DBT - Data Build Tool

Introduction to DBT

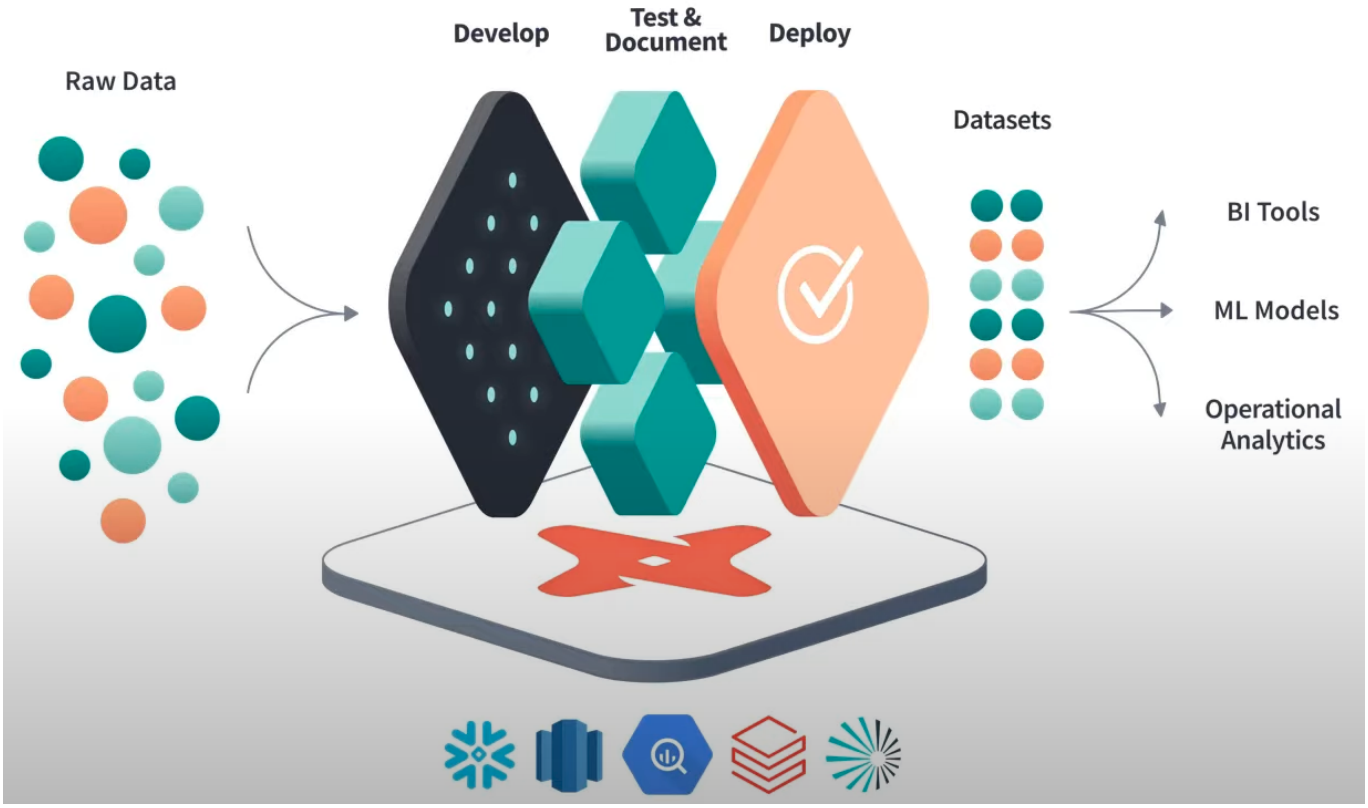
What is DBT?

DBT (Data Build Tool) is an SQL-based transformation tool that enables data engineers and analysts to transform data inside a data warehouse. It is widely used to implement ELT (Extract-Load-Transform) workflows.

Unlike traditional ETL (Extract-Transform-Load) tools, DBT does not extract or load data; instead, it focuses only on the transformation step. It allows users to write modular SQL code, apply version control using Git, and ensure data quality through testing.

Why Use DBT?

- Automated Data Transformations: Standardizes and simplifies SQL-based data transformations.
- Improves Data Quality: Implements tests to validate data before usage.
- Modular & Scalable: Encourages a structured approach with staging, marts, and fact tables.
- Works Seamlessly with Data Warehouses: Optimized for cloud data warehouses like Snowflake, BigQuery, and Redshift.
- Integrates with Git & CI/CD Pipelines: Supports version control and automated deployments.



ETL or ELT???

Understanding ELT vs. ETL

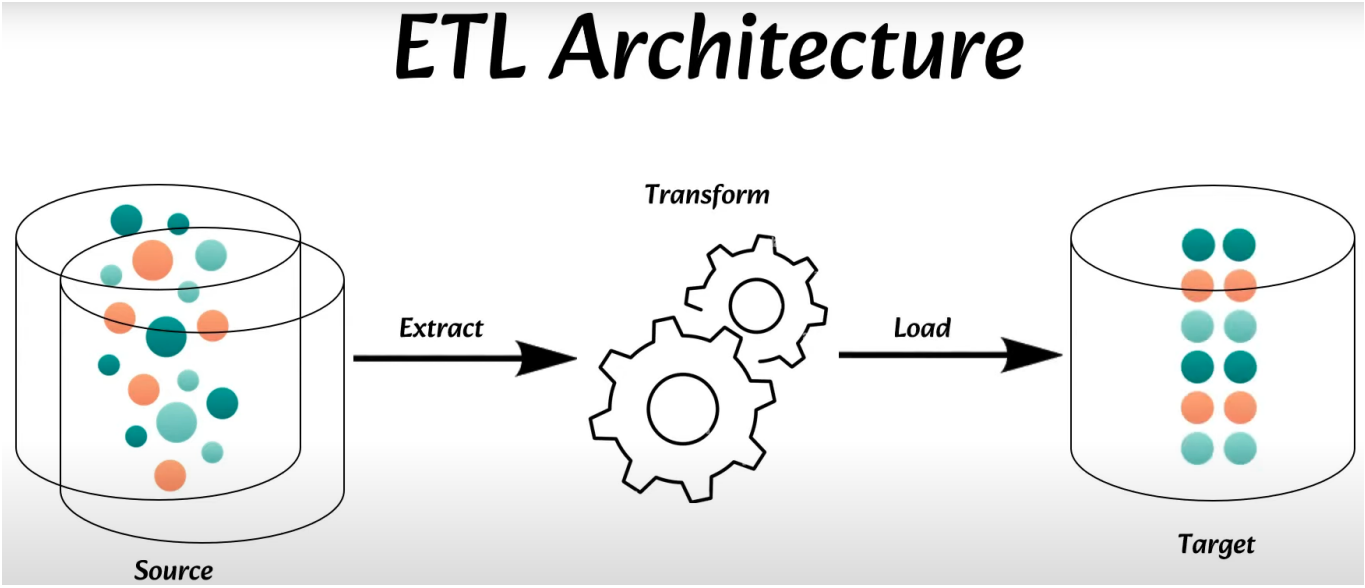
ETL (Extract-Transform-Load)

- Data is extracted from sources, transformed in an external processing environment, and then loaded into the data warehouse.
- Disadvantages: Complex processing pipelines, costly infrastructure for transformation, and slower query performance.

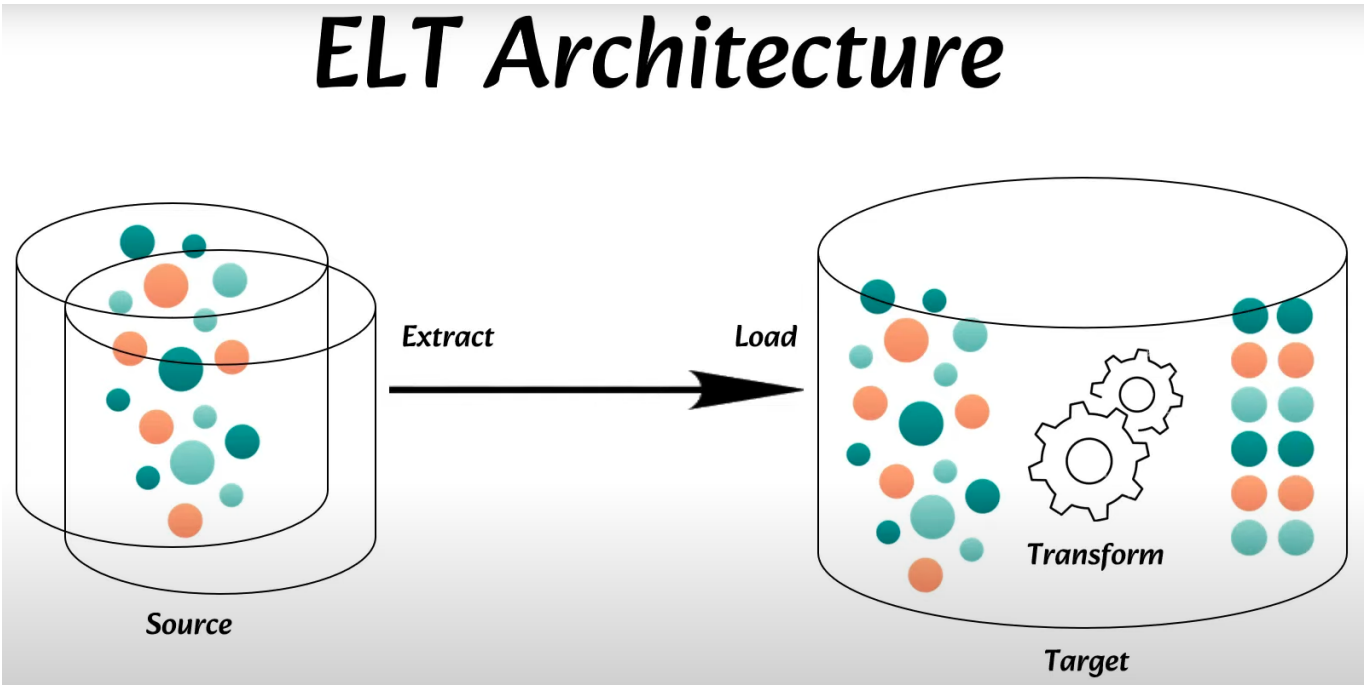
ELT (Extract-Load-Transform)

- Data is extracted and loaded as raw data into the warehouse first.
- Transformations occur inside the data warehouse, leveraging its computing power.
- Advantages: Cost-efficient, scalable, and allows for more flexible transformations.

ETL



ELT



DBT is optimized for ELT workflows, making it an essential tool for modern cloud-based data warehousing.

Explanation of DBT Project Structure

models/ - Contains SQL models for data transformations. Organized into subfolders.

models/staging/ - Contains staging models that clean and standardize raw data.

models/marts/ - Stores the final transformed tables (fact & dimension tables).

models/intermediate/ - Intermediate transformations used between staging and marts.

tests/ - Contains custom SQL-based singular tests. Generic Tests (Built-in): These tests validate column constraints. Singular Tests (Custom SQL): Singular tests use custom queries to validate business rules.

macros/ - Stores reusable SQL logic functions.

seeds/ - Holds static CSV data that DBT can import into Snowflake.

snapshots/ - Tracks historical changes in data (slowly changing dimensions).

dbt_project.yml - Main DBT configuration file.

profiles.yml - Stores database connection details.

Types of DBT Models

1. Staging Models (stg_*)
    - Purpose: Cleans and standardizes raw data before further transformations.
    - Why? Ensures data is formatted properly for downstream transformations.
    - Stored as: Views (not tables) for better performance.
2. Intermediate Models (int_*)
    - Purpose: Aggregates data from staging models before creating final marts.
    - Why? Helps in organizing reusable logic before the final reporting tables.
    - Stored as: Either tables or views.
3. Marts Models (fct_* and dim_*)

Fact Tables (fct_*)

```
- Contains numeric metrics and transactional data (e.g., total sales,
revenue).
- Why? Helps with analytical queries and reporting.
```

Dimension Tables (dim_*)

```
- Contains descriptive attributes (e.g., customer names, product
categories).
```

```
- Why? Helps in slicing and dicing the data for analysis.
```

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1. Installation of DBT

```
pip install dbt-core dbt-snowflake
```

Setup snowflake environment

This is to be run in the snowflake workbook

```
-- create accounts
use role accountadmin;
create warehouse dbt_wh with warehouse_size='x-small';
create database if not exists dbt_db;
create role if not exists dbt_role;

show grants on warehouse dbt_wh;

grant role dbt_role to user jayzern;
grant usage on warehouse dbt_wh to role dbt_role;
grant all on database dbt_db to role dbt_role;

use role dbt_role;

create schema if not exists dbt_db.dbt_schema;

-- clean up
use role accountadmin;

drop warehouse if exists dbt_wh;
drop database if exists dbt_db;
drop role if exists dbt_role;
```

2. DBT Project Initialization

- Command to Start a DBT Project

```
dbt init
```

Steps after the above command

- name: data_pipeline
- db: Snowflake
- Account & Password for Snowflake

- role: dbt_role
- warehouse: dbt_wh
- db: dbt_db
- schema: dbt_schema
- threads: 10 (can give anything)

3. Configuring dbt_profile.yaml

- Main file for the dbt-project.

```
models:
  snowflake_workshop:
    staging:
      materialized: view
      snowflake_warehouse: dbt_wh
    marts:
      materialized: table
      snowflake_warehouse: dbt_wh
```

- Create new folders in models- staging and marts
- Creation of few tables and views i.e., staging and marts

Before proceeding let's get a few necessary packages for our transformations

- Installing 3rd party libraries
- Create new fodler packages.yaml

```
packages:
  - package: 'dbt-labs/dbt_utils'
    version: '1.3.0'
```

- Install Packages

```
dbt deps
```

4. Setup Source and Staging files

models/staging/tpch_sources.yml

```
version: 2

sources:
  - name: tpch
    database: snowflake_sample_data
    schema: tpch_sf1
```

```
    tables:
      - name: orders
        columns:
            # writing a few tests here to validate Generic tests
          - name: o_orderkey
            tests:
              - unique
              - not_null
      - name: lineitem
        columns:
          - name: l_orderkey # foreign key check using the test
            tests:
              - relationships:
                  to: source('tpch', 'orders')
                  field: o_orderkey
```

Create **models/staging/stg_tpch_orders.sql**

```
select
*
from
    {{ source('tpch', 'orders') }}
```

Run the created file and check if the table is created in snowflake or not

```
dbt run
```

Modify the stg_tpch_orders.sql and run again

```
select
    o_orderkey as order_key,
    o_custkey as customer_key,
    o_orderstatus as status_code,
    o_totalprice as total_price,
    o_orderdate as order_date
from
    {{ source('tpch', 'orders') }}
```

```
dbt run -s stg_tpch_orders.sql
```

Create one more view for line_items **models/staging/tpch/stg_tpch_line_items.sql**

```
select
    {{
        dbt_utils.generate_surrogate_key([
            'l_orderkey',
            'l_linenumber'
        ])
    }} as order_item_key,
    l_orderkey as order_key,
    l_partkey as part_key,
    l_linenumber as line_number,
    l_quantity as quantity,
    l_extendedprice as extended_price,
    l_discount as discount_percentage,
    l_tax as tax_rate
from
    {{ source('tpch', 'lineitem') }}
```

```
dbt run -s stg_tpch_line_items.sql
```

5. Transformations on Staging tables

- Performs a few computations on the line items tables and create fact tables. (these are used in Dimensional Modeling, these are the tables that contain data about the numeric measures by operations on raw data.)

Macros Creation

- Reusable logic across different files

macros/pricing.sql

```
{% macro discounted_amount(extended_price, discount_percentage, scale=2)
%}
    (-1 * {{extended_price}} * {{discount_percentage}})::decimal(16, {{
scale }})
{% endmacro %}
```

Transformations

Create file **models/marts/int_order_items.sql**

```
select
    line_item.order_item_key,
    line_item.part_key,
```

```
    line_item.line_number,
    line_item.extended_price,
    orders.order_key,
    orders.customer_key,
    orders.order_date,
    {{ discounted_amount('line_item.extended_price',
'line_item.discount_percentage') }} as item_discount_amount
from
    {{ ref('stg_tpch_orders') }} as orders
join
    {{ ref('stg_tpch_line_items') }} as line_item
        on orders.order_key = line_item.order_key
order by
    orders.order_date
```

```
dbt run -s int_order_items
```

Creation of other intermediate files

marts/int_order_items_summary.sql

```
select
    order_key,
    sum(extended_price) as gross_item_sales_amount,
    sum(item_discount_amount) as item_discount_amount
from
    {{ ref('int_order_items') }}
group by
    order_key
```

Creation of a fact model **models/marts/fct_orders.sql**

```
select
    orders.*,
    order_item_summary.gross_item_sales_amount,
    order_item_summary.item_discount_amount
from
    {{ref('stg_tpch_orders')}} as orders
join
    {{ref('int_order_items_summary')}} as order_item_summary
        on orders.order_key = order_item_summary.order_key
order by order_date
```

```
dbt run
```

- CHECK SNOWFLAKE, Tables are created in snowflake

6. Testing

Generic Test creation in marts folder

models/marts/generic_tests.yml

```
models:
  - name: fct_orders
    columns:
      - name: order_key
        tests:
          - unique
          - not_null
          - relationships:
              to: ref('stg_tpch_orders')
              field: order_key
              severity: warn
      - name: status_code
        tests:
          - accepted_values:
              values: ['P', 'O', 'F']
```

```
dbt test
```

Singular Tests

- Check if the discount amount is always greater than zero or not.

tests/fct_orders_discount.sql

```
select
    *
from
    {{ref('fct_orders')}}
where
    item_discount_amount > 0
```

- One more singular test to make sure the order date is in a specific range

tests/fct_orders_date_valid.sql

```
select
    *
from
    {{ref('fct_orders')}}
where
    date(order_date) > CURRENT_DATE()
    or date(order_date) < date('1990-01-01')
```

7. DBT Documentation & Lineage Graph

Generate DBT documentation so students can explore DBT model relationships.

```
dbt docs generate
dbt docs serve
```

8. Deploying on Airflow

why are we using Astronomer-Cosmos?

- Provides a wrapper for DBT inside Airflow DAGs.
- Simplifies running DBT without writing complex BashOperator scripts.

Steps for Airflow Deployment

1. Command to install astro library

```
brew install astro
```

Astro Installation Guide

Check if you have successfully installed ASTRO or not

```
astro version
```

2. Initialize Airflow project - astro

Guide for deploying AIRFLOW for DBT using ASTRO

```
astro dev init
```

The above command creates a new astro project.

3. Navigate into the astro directory, modify the docker file and requirements.txt as below

DOCKERFILE

```
FROM quay.io/astronomer/astro-runtime:11.3.0

# install dbt into a virtual environment
RUN python -m venv dbt_venv && source dbt_venv/bin/activate && \
    pip install --no-cache-dir dbt-snowflake && deactivate
```

Requirements.txt

```
astronomer-cosmos
apache-airflow-providers-snowflake
```

4. Move your dbt project into DAGS directory

Sample directory structure

```
├── dags/
│   ├── dbt/
│   │   └── my_dbt_project/
│   │       ├── dbt_project.yml
│   │       ├── models/
│   │       │   ├── my_model.sql
│   │       │   └── my_other_model.sql
│   │       └── macros/
│   │           ├── my_macro.sql
│   │           └── my_other_macro.sql
│   └── my_cosmos_dag.py
├── Dockerfile
├── requirements.txt
```

5. Write a Dag file create a DAG file in the dag folder with any name "my_cosmos_dag.py"

DAG File for Airflow

```
import os
from datetime import datetime

from cosmos import DbtDag, ProjectConfig, ProfileConfig, ExecutionConfig
from cosmos.profiles import SnowflakeUserPasswordProfileMapping


profile_config = ProfileConfig(
    profile_name="default",
    target_name="dev",
    profile_mapping=SnowflakeUserPasswordProfileMapping(
```

```
            conn_id="snowflake_conn",
            profile_args={"database": "dbt_db", "schema": "dbt_schema"},
        )
    )

    dbt_snowflake_dag = DbtDag(

    project_config=ProjectConfig("/usr/local/airflow/dags/dbt/data_pipeline",)
    ,
        operator_args={"install_deps": True},
        profile_config=profile_config,
        execution_config=ExecutionConfig(dbt_executable_path=f"
    {os.environ['AIRFLOW_HOME']}/dbt_venv/bin/dbt",),
        schedule_interval="@daily",
        start_date=datetime(2023, 9, 10),
        catchup=False,
        dag_id="dbt_dag",
    )
```

6. Start Airflow

- run the following command to start the airflow server (Airflow docker container)

```
astro dev start
```

`You'll get the airflow credentials in your terminal`

Once you login you should be able to see the dag we have created. Now setup up your snowflake connection in the Airflow UI by filling the following details

7. Establish Snowflake Connection in Airflow UI

Navigate to `ADMIN>CONNECTIONS`

```
Connection_id: snowflake_conn

Connection type: Snowflake

Snowflake Schema: dbt_schema

Login: < USER NAME>

Password: <PASSWORD>

Account: <YOUR ACCOUNT IDENTIFIER>

Warehouse: dbt_wh

Database: dbt_db
```

```
Role: dbt_role
```

Finally Trigger The DAG!!!!!