Project Documentation: Sales ETL Pipeline

1. Project Overview

This project implements an ETL pipeline to extract, validate, transform, and model sales data to ensure it is clean, consistent, and ready for analytical and reporting use cases.

2. ETL Process

2.1 Extract Phase

- Sales data was provided in **flattened JSON format**.
- The dataset was loaded into a **Pandas DataFrame**.
- **UTF-8 encoding** was applied to avoid character encoding issues.

2.2 Schema Validation

- Each record was validated against a predefined schema.
- Records were checked for unmapped or unexpected fields.
- **No schema violations were detected.**

Result:
The dataset fully conforms to the expected structure.

2.3 Data Exploration & Profiling

Exploratory Data Analysis (EDA) included:

- Dataset shape and data type inspection
- Null value analysis
- Duplicate detection

Key Findings:

- OrderDate was not stored as a proper datetime type.
- Duplicate records were present.
- Name, Education, and Occupation contain ~63% null values.

2.4 Distribution Analysis – Net Price

- Distribution was analyzed using boxplots and histograms.
- NetPrice showed a **right-skewed distribution** with high-value transactions.

- These values were retained as valid, representing premium products aligned with business expectations.

2.5 Data Quality & Redundancy Checks

- Column names and string values were checked for whitespace issues (none found).
- Redundant and low-quality attributes were identified:
    - Color duplicated Subcategory values and lacked semantic meaning.
    - CustomerKey and CustomerCode represented the same entity (1:1 relationship).

Decisions:

- Color and CustomerCode were removed.
- CustomerKey was retained due to better performance, join efficiency, and stability.

3. Transformation Phase

- Column names were standardized for consistency.
- OrderDate was converted to a proper datetime format.
- Duplicate handling was reviewed carefully:
    - Due to the absence of a unique order identifier or timestamp, duplicates were **retained** to avoid removing valid transactions.
- Columns with high null ratios and low analytical value were dropped:
    - Education
    - Occupation

4. Data Modeling & Loading Phase

The refined dataset was modeled using a **dimensional approach** to support analytical queries.

Product Dimension (dim_product)

- Attributes: ProductKey, ProductName, Brand, Subcategory, Category

Customer Dimension (dim_customer)

- Attributes: CustomerKey, Name
- Non-essential attributes were excluded for performance and relevance.

Geography Dimension (dim_geography)

- Attributes: City, State, CountryRegion, Continent
- A surrogate key (GeographyKey) was generated.

Date Dimension (dim_date)

- Derived from OrderDate
- Includes DateKey, Year, Month, MonthName, and Quarter

Sales Fact Table (fact_sales)

- Foreign keys: ProductKey, CustomerKey, GeographyKey, DateKey
- Measures: Quantity, NetPrice, SalesAmount

All tables were exported as CSV files and validated for row consistency.

5. Forecast Data Integration

- A clean forecast dataset covering **2008–2009** was integrated.
- Forecast values are provided by:
    - CountryRegion
    - Brand
    - Year
- No data quality issues were detected.

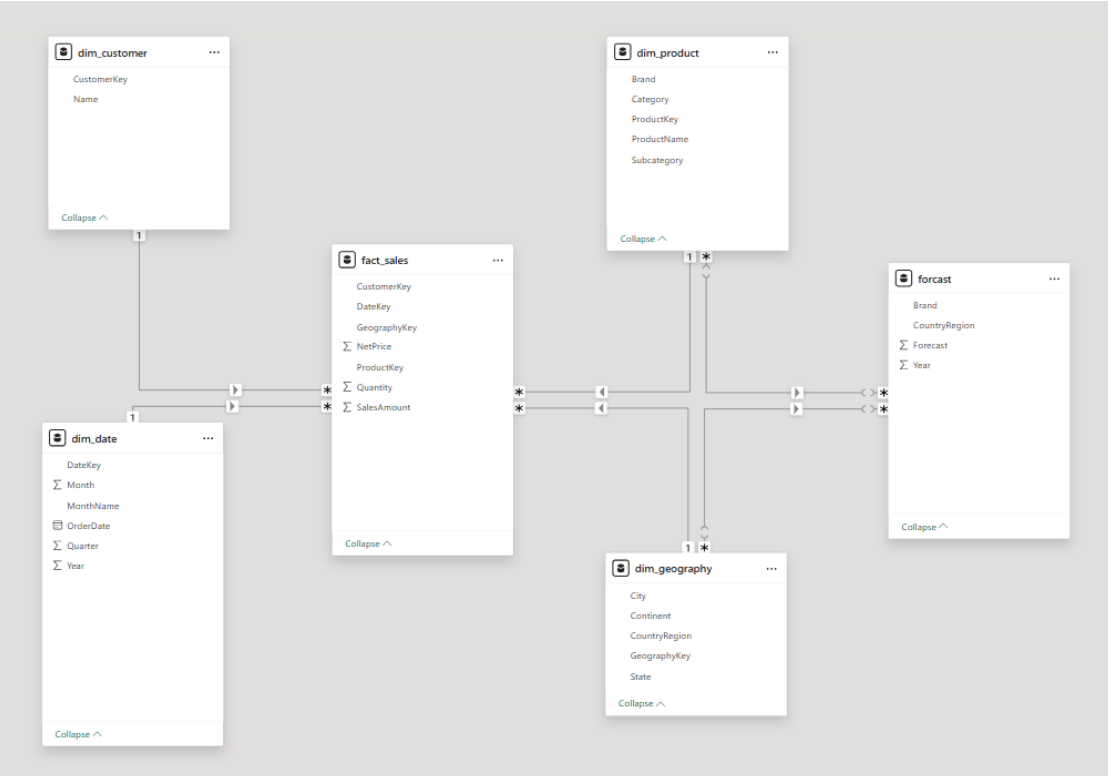
Use Cases:

- Forecast vs actual comparison
- Trend analysis
- Regional and brand-level performance evaluation

6. Data Model

The final architecture follows a **Fact Constellation (Galaxy Schema)**, where:

- Multiple fact tables (fact_sales, forecast) share common dimensions
- This design supports both transactional and planning analytics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CustomerKey
Name
Collapse
dim_product
Brand
Category
ProductKey
ProductName
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Collapse
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DateKey
GeographyKey
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ProductKey
Quantity
SalesAmount
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forcast
Brand
CountryRegion
Forecast
Year
Collapse
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MonthName
OrderDate
Quarter
Year
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dim_geography
City
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