E-Commerce (Target) DataWarehouse Report

1. Assignment Overview

This report presents the **design and implementation of a data warehouse** using **Microsoft Azure for data storage and Databricks for ETL and analytics**. The project involves **sourcing raw data, transforming it, and structuring it into a star schema** to facilitate analytical querying and business intelligence insights.

2. Data Sources

This dataset was sourced from the **Kaggle E-Commerce (Target) Sales Dataset**, which provides a detailed overview of Target's Brazilian operations and customer data. It includes information on **100,000 orders placed between 2016 and 2018**, covering aspects such as order status, pricing, payment, shipping performance, customer locations, product attributes, and customer reviews.

Dataset Overview

Target is a globally recognized brand and a leading retailer in the United States, known for offering exceptional value, innovation, and an unparalleled shopping experience. The dataset focuses on Target's Brazilian operations, providing valuable insights into business strategies and customer behavior.

Potential Use Cases:

- Understanding order processing and pricing strategies
- Evaluating payment and shipping efficiency
- Analyzing customer demographics and preferences
- Studying product characteristics and customer satisfaction

Dataset Files

The following datasets were used:

Dataset	File Name	Description
Customers	*customers.csv*	Contains customer details such as ID, location, and state.
Geolocation	*geolocation.csv*	Provides zip-code-based latitude and longitude information.
Orders	*orders.csv*	Includes order-related details such as status, timestamps, and estimated delivery dates.
Order Items	*order_items.csv*	Contains individual order item details such as product ID, seller ID, price, and freight cost.
Payments	*payments.csv*	Stores payment-related data such as payment type and amount paid.
Products	*products.csv*	Contains product information including category, weight, and dimensions.
Sellers	*sellers.csv*	Includes seller details such as seller ID, location, and state.

The full data dictionary, describing all fields in the dataset, is provided separately in the **README file** accompanying this report.

3. ETL Process Implementation

The ETL process follows the below steps:

3.1 Data Extraction

- The raw datasets stored in **Azure Blob Storage** are mounted to **Databricks**.
- Data is extracted using PySpark and stored in **staging tables** within **Databricks Delta Lake**.

3.2 Data Transformation

- **Data Cleaning:** Handling missing values, standardizing column names, and normalizing data types.
- **Handling Surrogate Keys:** Assigning unique identifiers (surrogate keys) for dimension tables.
- **Implementing Slowly Changing Dimensions (SCD Type 2):** Maintaining historical records for dimensions like customers, products and sellers.

3.3 Data Loading

- Transformed data is loaded into the **data warehouse using a star schema**.

4. Data Warehouse Design: Star Schema

4.1 Dimension Tables:

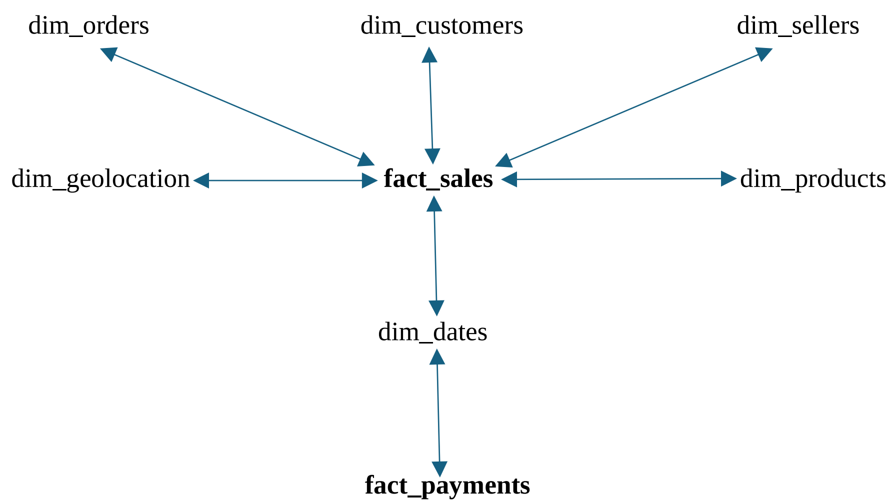
Table Name	Primary Key	Description
dim_customers	customer_key	Stores customer details with SCD Type 2 implementation.
dim_geolocation	geolocation_key	Contains geographic information for customers and sellers.
dim_products	product_key	Includes product details such as category, weight, and dimensions.
dim_sellers	seller_key	Stores seller information including location.
dim_dates	date_key	Maintains order dates, delivery dates, and other timestamps.
dim_orders	order_key	Stores order-level information such as order ID and status.

4.2 Fact Tables:

Table Name	Primary Key	Description
fact_sales	order_id	Stores sales transactions including price, freight, and shipping details.
fact_payments	order_id	Contains payment-related data such as amount and payment method.

4.3 Star Schema Design

Visual Representation of the Star Schema:



1. Fact Table: fact_sales

Primary Fact Table - Stores transaction-level sales data.
Connected to:

- **dim_customers** → To track which customer placed the order (customer_key).
- **dim_products** → To identify which products were sold (product_key).
- **dim_sellers** → To determine which seller sold the item (seller_key).
- **dim_dates** → To track order timestamps (order_date_key).
- **dim_orders** → To link order-specific details (order_key).
- **dim_geolocation** → To track location-based insights (geolocation_key).

2. Fact Table: fact_payments

Stores payment transactions for each order. Since the dataset does not provide an explicit **payment date**, we assume that **payment is made on the order purchase date** (from staging_orders).
Connected to:

- **fact_sales** → Payments belong to orders (order_id).
- **dim_dates** → Payment dates (date_key).

3. Dimension Tables:

Dimension	Linked to Fact Table(s)	Purpose
dim_customers	fact_sales	Tracks customer details using customer_key.
dim_products	fact_sales	Provides product-specific attributes.
dim_sellers	fact_sales	Identify the seller for each sale.
dim_dates	fact_sales, fact_payments	Used for date-based filtering and trends.
dim_orders	fact_sales	Stores order status and metadata.
dim_geolocation	fact_sales	Enables location-based analytics.

This structure ensures **optimized analytical querying** while maintaining **data integrity and reducing redundancy**.

5. Analytical Querying and Business Insights

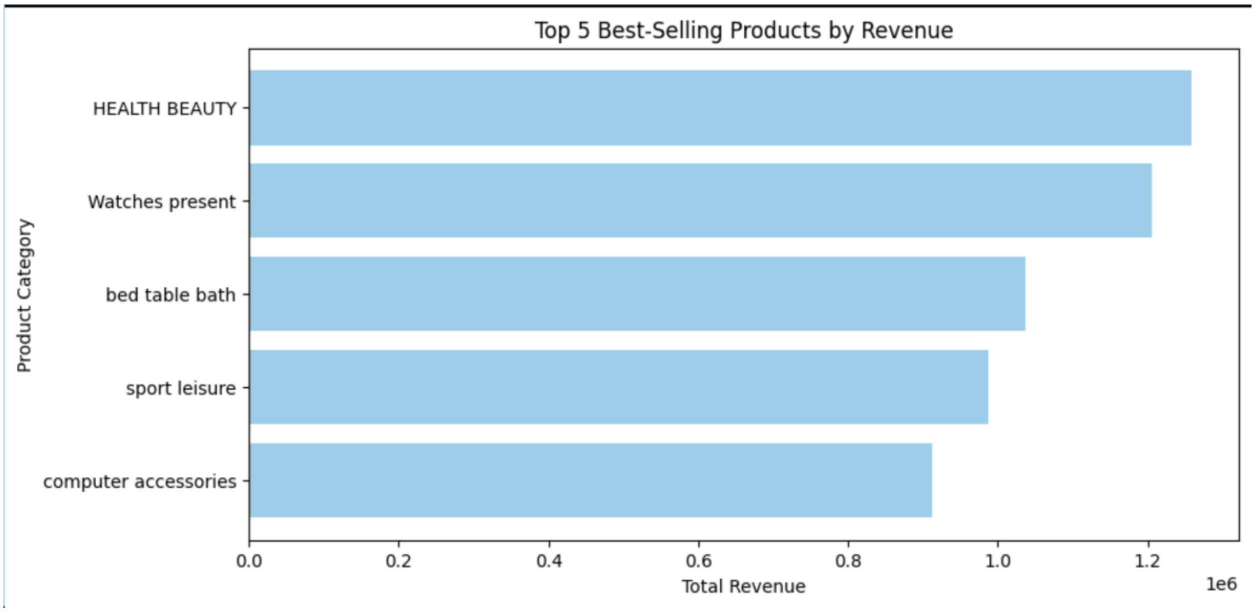
5.1 Query 1: Top 5 Best-Selling Product Categories

Use Case: Helping businesses optimize their product strategy, inventory management, and marketing campaigns.

```
import matplotlib.pyplot as plt

df_best_products = spark.sql("""
SELECT p.product_category,
       ROUND(SUM(s.price)) AS total_revenue
FROM fact_sales s
JOIN dim_products p ON s.product_key = p.product_key
GROUP BY p.product_category
ORDER BY total_revenue DESC
LIMIT 5
""").toPandas()

plt.figure(figsize=(10, 5))
plt.barh(df_best_products["product_category"], df_best_products["total_revenue"], color="skyblue")
plt.xlabel("Total Revenue")
plt.ylabel("Product Category")
plt.title("Top 5 Best-Selling Products by Revenue")
plt.gca().invert_yaxis()
plt.show()
```

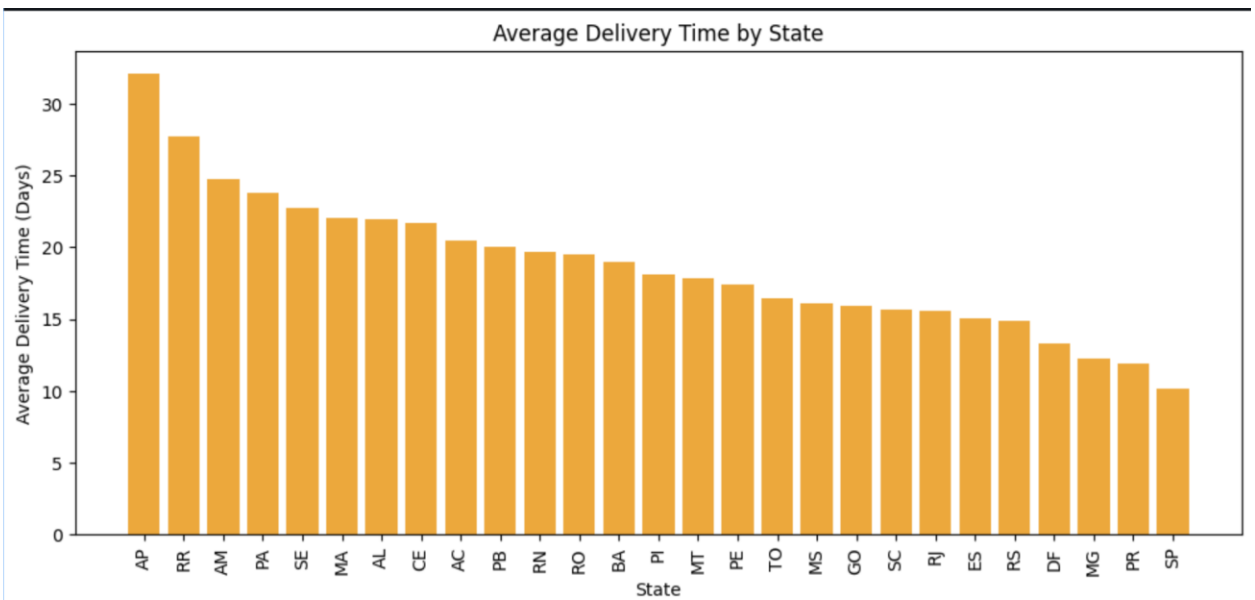


5.2 Query 2: Average Delivery Time by State

Use Case: Helping businesses improve logistics efficiency, optimize delivery routes, and enhance customer satisfaction.

```
df_delivery_time = spark.sql("""
SELECT g.state,
    ROUND(AVG(DATEDIFF(f.order_delivered_customer_date, f.order_purchase_timestamp)), 2) AS
avg_delivery_time
FROM fact_sales f
JOIN dim_customers c ON f.customer_key = c.customer_key
JOIN dim_geolocation g ON c.customer_zip_code_prefix = g.zip_code_prefix
WHERE f.order_delivered_customer_date IS NOT NULL
GROUP BY g.state
ORDER BY avg_delivery_time DESC
""").toPandas()

# Bar Chart
plt.figure(figsize=(12, 5))
plt.bar(df_delivery_time["state"], df_delivery_time["avg_delivery_time"], color="orange")
plt.xlabel("State")
plt.ylabel("Average Delivery Time (Days)")
plt.title("Average Delivery Time by State")
plt.xticks(rotation=90)
plt.show()
```

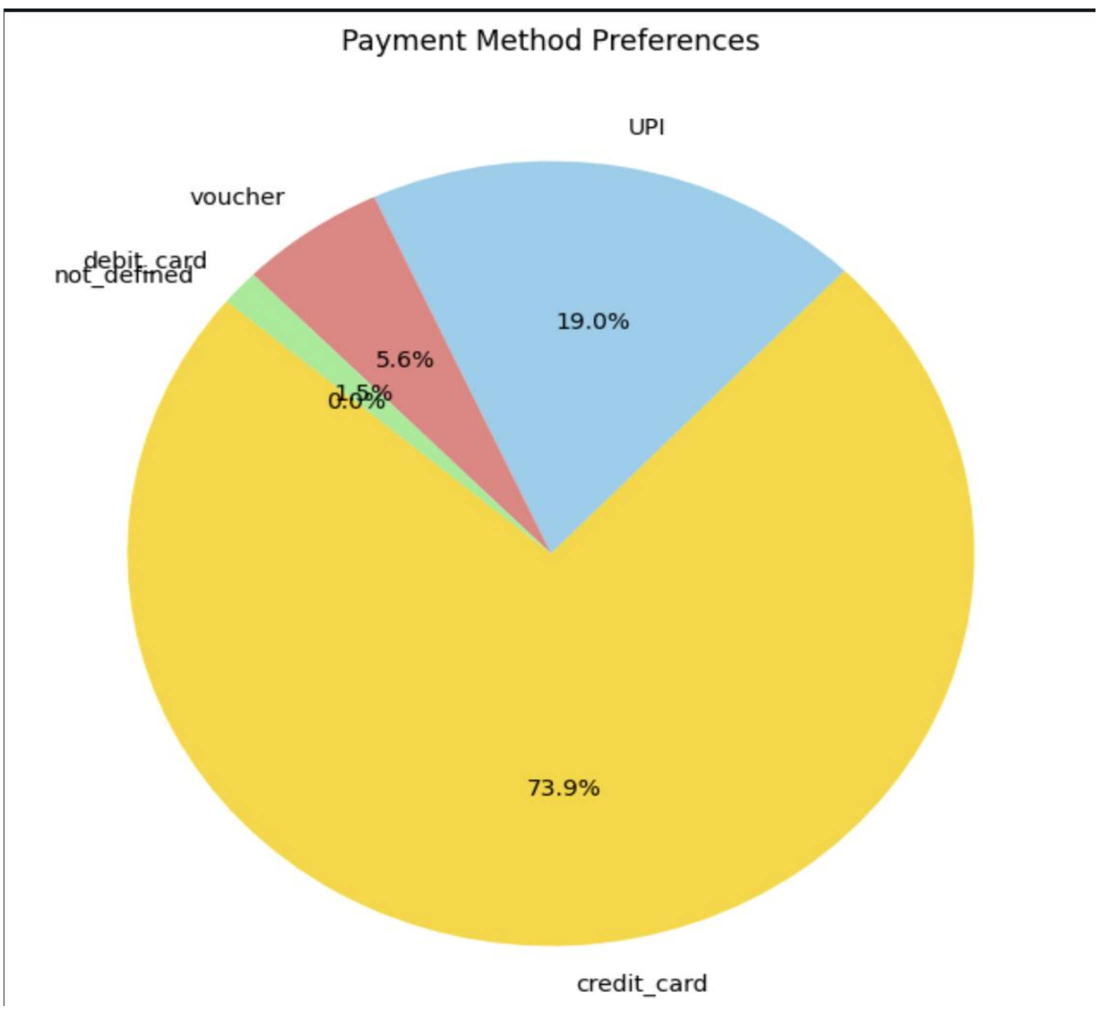


5.3 Query 3: Payment Method Preferences

Use Case: Helping businesses understand customer payment preferences to optimize payment options and enhance the checkout experience.

```
df_payment_methods = spark.sql("""
SELECT p.payment_type,
    ROUND(COUNT(p.order_id)) AS total_transactions
FROM fact_payments p
GROUP BY p.payment_type
ORDER BY total_transactions DESC
""").toPandas()

plt.figure(figsize=(8, 8))
plt.pie(df_payment_methods["total_transactions"], labels=df_payment_methods["payment_type"],
autopct="%1.1f%%", startangle=140, colors=["gold", "skyblue", "lightcoral", "lightgreen"])
plt.title("Payment Method Preferences")
plt.show()
```



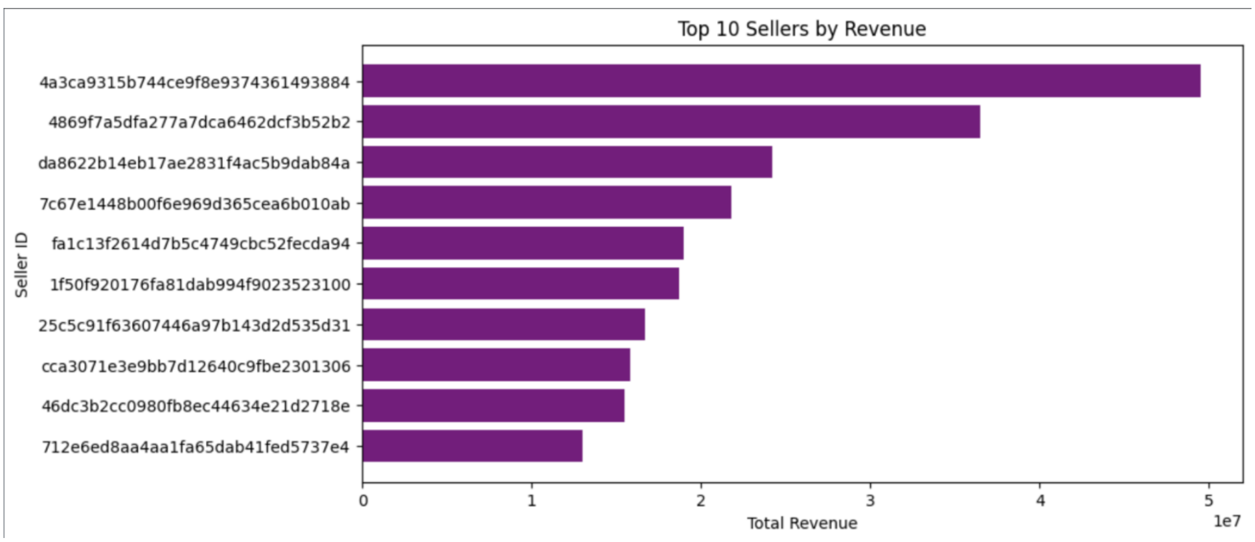
5.4 Query 4: Top 10 Sellers by Revenue

Use Case: Helping businesses identify top-performing sellers and optimize partnerships to drive higher revenue and sales growth.

Note: Since there is no Name attribute in the dataset, SellerID is used for representation.

```
df_top_sellers = spark.sql("""
SELECT s.seller_id,
    g.city,
    g.state,
    ROUND(SUM(f.price)) AS total_revenue
FROM fact_sales f
JOIN dim_sellers s ON f.seller_key = s.seller_key
JOIN dim_geolocation g ON s.seller_zip_code_prefix = g.zip_code_prefix
GROUP BY s.seller_id, g.city, g.state
ORDER BY total_revenue DESC
LIMIT 10
""").toPandas()

plt.figure(figsize=(10, 5))
plt.barh(df_top_sellers["seller_id"], df_top_sellers["total_revenue"], color="purple")
plt.xlabel("Total Revenue")
plt.ylabel("Seller ID")
plt.title("Top 10 Sellers by Revenue")
plt.gca().invert_yaxis()
plt.show()
```

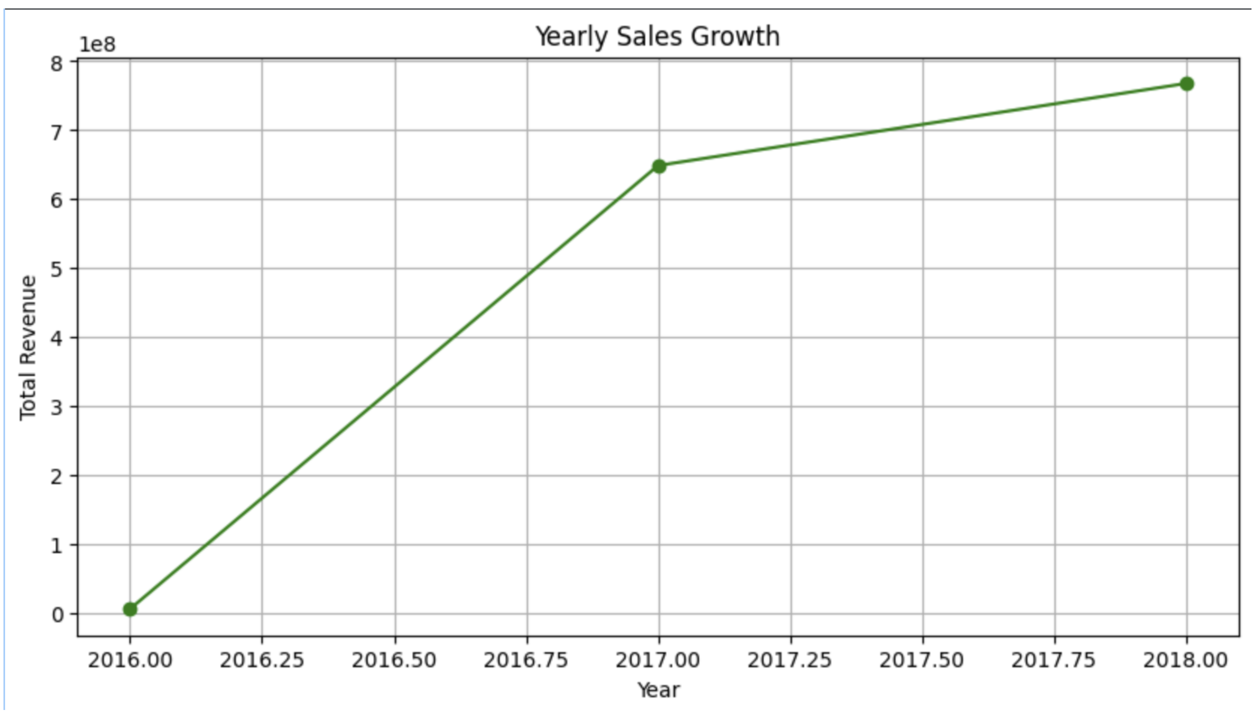


5.5 Query 5: Yearly Sales Growth

Use Case: Helping businesses analyze yearly sales performance trends, measure growth rates, and make data-driven decisions for future revenue strategies.

```
df_yearly_sales = spark.sql("""
SELECT d.year,
    ROUND(SUM(f.price), 0) AS total_revenue,
    LAG(ROUND(SUM(f.price), 0)) OVER (ORDER BY d.year) AS previous_year_revenue,
    ROUND(
      ((ROUND(SUM(f.price), 0) - LAG(ROUND(SUM(f.price), 0)) OVER (ORDER BY d.year))
      / LAG(ROUND(SUM(f.price), 0)) OVER (ORDER BY d.year)) * 100, 2
    ) AS growth_rate
FROM fact_sales f
JOIN dim_dates d ON f.order_date_key = d.date_key
GROUP BY d.year
ORDER BY d.year
""").toPandas()

# Line Chart
plt.figure(figsize=(10, 5))
plt.plot(df_yearly_sales["year"], df_yearly_sales["total_revenue"], marker="o", linestyle="-", color="green")
plt.xlabel("Year")
plt.ylabel("Total Revenue")
plt.title("Yearly Sales Growth")
plt.grid()
plt.show()
```



6. Conclusion and Future Improvements

This data warehouse implementation successfully provides **scalable, efficient, and insightful analytics**. Future enhancements could include:

- **Integrating machine learning models** for demand forecasting.
- **Optimizing query performance** using indexing and materialized views.
- **Automating ETL workflows** with Apache Airflow.