End-to-End Data Engineering Pipeline on Azure Databricks | Retail Analytics Data Warehouse

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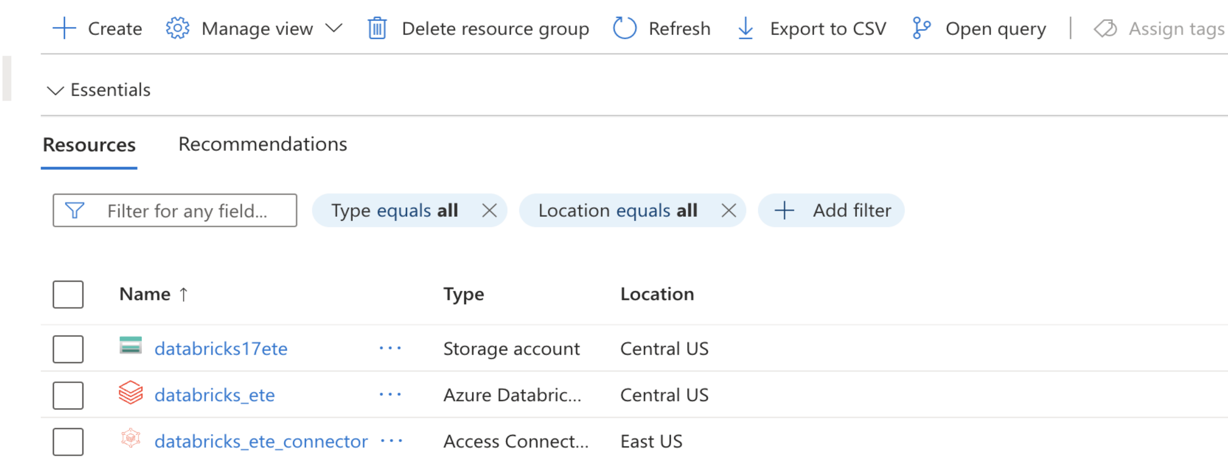
1. Project Objective

Built a production-grade, cloud-native data engineering pipeline on Azure Databricks using the **Medallion Architecture** (Bronze → Silver → Gold) to create a scalable retail analytics data warehouse. Implemented incremental ingestion, SCD Type 1 & Type 2, data quality checks, orchestration, and Power BI reporting to support historical tracking and business decision-making.

Tech Stack: Azure Databricks (PySpark, Delta Lake, Delta Live Tables), Azure Data Lake Gen2, Unity Catalog, Databricks Workflows, Power BI



Azure Data Lake, Databricks, Databricks connector

2. Dataset Overview

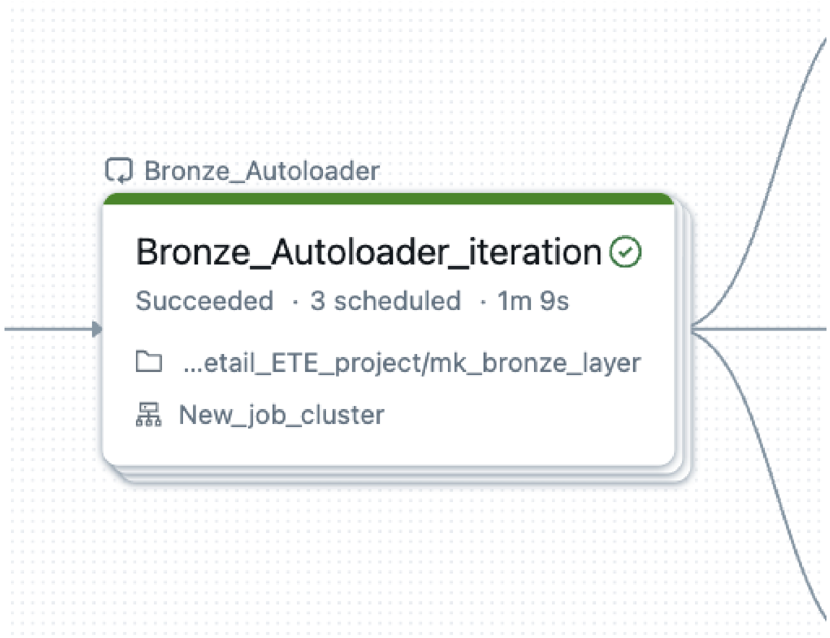
- Rows: ~12,500 incremental transactions (initial load ~10K orders + daily incremental files)

- Key Entities: Orders, Customers, Products, Regions

Key Dimensions & Measures

- Customer: customer_id, full_name, email, domain, registration_date
- Product: product_id, product_name, category, brand, price, discounted_price
- Orders: order_id, order_date, quantity, total_amount
- Region: region_id, region_name

Data Quality Note: Schema evolution and malformed records handled via Autoloader rescued_data column



Autoloader

Nov 25, 2025 (1s) 4

```
df.display()
```

(2) Spark Jobs

Table +

	r_id	first_name	last_name	email	city	state	_rescued_data
1		Emily	Mooney	rushjeff@ryan.org	Johnsonmouth	MS	null
2		Andrea	Sellers	mccoykiara@kelly.com	Stephenfort	WY	null
3		Craig	Hayes	rebeccamiller@yahoo.com	South Stephenshire	LA	null
4		Bryan	Scott	lawrence05@campbell.info	Chrisland	ND	null
5		Sean	Vasquez	carrie45@yahoo.com	East Dennistown	RI	null
6		Kevin	Mccarthy	traceyramos@gmail.com	North Matthew	IN	null
7		Amanda	Doyle	scottallen@gmail.com	Joneshaven	VA	null
8		Paul	Campos	sullivanjeremy@horton-adams.com	South Nathanfurt	CT	null
9		Mary	Green	dennis03@yahoo.com	Kimberlyview	MD	null
10		James	Myers	charles58@murillo.net	West Hector	OK	null
11		Jacob	Le	anita65@gmail.com	Houstonfurt	AR	null

rescued_data column

3. Data Engineering & ETL Pipeline (PySpark + Delta Lake + DLT)

Extract & Load (Bronze Layer)

- Used **Databricks Auto Loader** (cloudFiles) for schema inference and incremental ingestion from ADLS Gen2
- Raw Parquet files → Bronze Delta tables with checkpointing for exactly-once processing

Data Reading

Nov 20, 2025 (1s) 5

```
df = spark.readStream.format("cloudFiles")\
        .option("cloudFiles.format","parquet")\
        .option("cloudFiles.schemaLocation",f"abfss://bronze@databricks17ete.dfs.core.windows.net/checkpoint_{p_file_name}
        ")\
        .load(f"abfss://source@databricks17ete.dfs.core.windows.net/{p_file_name}")
```

df: pyspark.sql.dataframe.DataFrame = [order_id: string, customer_id: string ... 5 more fields]

Databricks Auto Loader reading new Parquet files from ADLS Gen2 into a streaming DataFrame

Nov 25, 2025 (1s) 4

```
df.display()
```

(2) Spark Jobs

Table

	r_id	first_name	last_name	email	city	state	_rescued_data
1		Emily	Mooney	rushjeff@ryan.org	Johnsonmouth	MS	null
2		Andrea	Sellers	mccoykiara@kelly.com	Stephenfort	WY	null
3		Craig	Hayes	rebeccamiller@yahoo.com	South Stephenshire	LA	null
4		Bryan	Scott	lawrence05@campbell.info	Chrisland	ND	null
5		Sean	Vasquez	carrie45@yahoo.com	East Dennistown	RI	null
6		Kevin	Mccarthy	traceyramos@gmail.com	North Matthew	IN	null
7		Amanda	Doyle	scottallen@gmail.com	Joneshaven	VA	null
8		Paul	Campos	sullivanjeremy@horton-adams.com	South Nathanfurt	CT	null
9		Mary	Green	dennis03@yahoo.com	Kimberlyview	MD	null
10		James	Myers	charles58@murillo.net	West Hector	OK	null
11		Jacob	Le	anita65@gmail.com	Houstonfurt	AR	null

_rescued_data column displayed

Silver_Orders

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```
df.printSchema()
```

```
root
 |-- order_id: string (nullable = true)
 |-- customer_id: string (nullable = true)
 |-- product_id: string (nullable = true)
 |-- order_date: date (nullable = true)
 |-- quantity: integer (nullable = true)
 |-- total_amount: double (nullable = true)
 |-- _rescued_data: string (nullable = true)
```

table schema

Transform (Silver Layer – Cleaning & Enrichment)

- Removed duplicates using window functions (row_number)
- Extracted domain from email, created full_name, applied 10% discount logic
- Added data quality expectations with @dlt.expect_or_drop / @dlt.expect_or_fail

▶ ✓ Nov 25, 2025 (1s) 6

```
df = df.withColumn("domains", split(col('email'), '@')[1])
df.display()
```

▸ (2) Spark Jobs

▸ df: pyspark.sql.dataframe.DataFrame = [customer_id: string, first_name: string ... 5 more fields]

Table +

	ner_id	first_name	last_name	email	city	state	domains
1		Emily	Mooney		Johnsonmouth	MS	ryan.org
2		Andrea	Sellers		Stephenfort	WY	kelly.com
3		Craig	Hayes		South Stephenshire	LA	yahoo.com
4		Bryan	Scott		Chrisland	ND	campbell.info
5		Sean	Vasquez		East Dennistown	RI	yahoo.com
6		Kevin	Mccarthy		North Matthew	IN	gmail.com
7		Amanda	Doyle		Joneshaven	VA	gmail.com
8		Paul	Campos		South Nathanfurt	CT	horton-adams.com
9		Mary	Green		Kimberlyview	MD	yahoo.com

extracting email domains into a new "domains" column

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```
df = df.withColumn("full_name", concat(col("first_name"), lit(" "), col("last_name")))
df = df.drop("first_name","last_name")

df.display()
```

▸ (2) Spark Jobs

▸ df: pyspark.sql.dataframe.DataFrame = [customer_id: string, email: string ... 4 more fields]

Table +

	customer_id	email	city	state	domains	full_name
1	C00001		Johnsonmouth	MS	ryan.org	Emily Mooney
2	C00002		Stephenfort	WY	kelly.com	Andrea Sellers
3	C00003		South Stephenshire	LA	yahoo.com	Craig Hayes
4	C00004		Chrisland	ND	campbell.info	Bryan Scott
5	C00005		East Dennistown	RI	yahoo.com	Sean Vasquez
6	C00006		North Matthew	IN	gmail.com	Kevin Mccarthy
7	C00007		Joneshaven	VA	gmail.com	Amanda Doyle
8	C00008		South Nathanfurt	CT	horton-adams.com	Paul Campos
9	C00009		Kimberlyview	MD	yahoo.com	Mary Green

Concatenating two columns into a full name column

Nov 25, 2025 (17s) 8

```python
df_gmail = df.filter(col('domains')=="gmail.com")
df_gmail.display()
time.sleep(5)

df_yahoo = df.filter(col('domains')=="yahoo.com")
df_yahoo.display()
time.sleep(5)

df_hotmail = df.filter(col('domains')=="hotmail.com")
df_hotmail.display()
time.sleep(5)
```

(6) Spark Jobs

df_gmail: pyspark.sql.dataframe.DataFrame = [customer_id: string, first_name: string ... 5 more fields]

df_hotmail: pyspark.sql.dataframe.DataFrame = [customer_id: string, first_name: string ... 5 more fields]

df_yahoo: pyspark.sql.dataframe.DataFrame = [customer_id: string, first_name: string ... 5 more fields]

Table

	customer_id	first_name	last_name	email	city	state	domains
1	C00006	Kevin	Mccarthy	traceyramos@gmail.com	North Matthew	IN	gmail.com
2	C00007	Amanda	Doyle	scottallen@gmail.com	Joneshaven	VA	gmail.com

PySpark code filtering and displaying DataFrame rows by email domain

Silver_Orders

Python Excluded Tabs: ON Last edit was 5 days ago

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```python
df1 = df.withColumn("flag",dense_rank().over(Window.partitionBy("year").orderBy(desc
("total_amount"))))
df1.display()
```

(2) Spark Jobs

df1: pyspark.sql.dataframe.DataFrame = [order_id: string, customer_id: string ... 6 more fields]

Table

	order_id	customer_id	product_id	order_date	quantity
1	O00957	C01449	P0498	2023-10-05T00:00:00.000+00:00	5
2	O01765	C01515	P0498	2023-05-11T00:00:00.000+00:00	5
3	O03502	C00805	P0498	2023-09-24T00:00:00.000+00:00	5
4	O03660	C01001	P0498	2023-10-08T00:00:00.000+00:00	5
5	O06790	C01819	P0498	2023-02-27T00:00:00.000+00:00	5
6	O03989	C00631	P0440	2023-11-20T00:00:00.000+00:00	5
7	O07763	C00471	P0440	2023-04-12T00:00:00.000+00:00	5
8	O03272	C01879	P0165	2023-02-15T00:00:00.000+00:00	5
9	O03746	C01713	P0165	2023-10-26T00:00:00.000+00:00	5

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dense_rank() window function to flag top-spending orders per year by total amount

Nov 25, 2025 (3s) 7

```
df.groupBy("domains").agg(count("customer_id").alias("total_customers")).orderBy(desc
("total_customers")).display()
```

(2) Spark Jobs

Table

	domains	total_customers
1	gmail.com	374
2	hotmail.com	360
3	yahoo.com	331
4	brown.com	8
5	davis.com	8
6	smith.com	7
7	hernandez.com	5
8	johnson.com	5

Counts distinct customers per email domain and shows the top domains by count

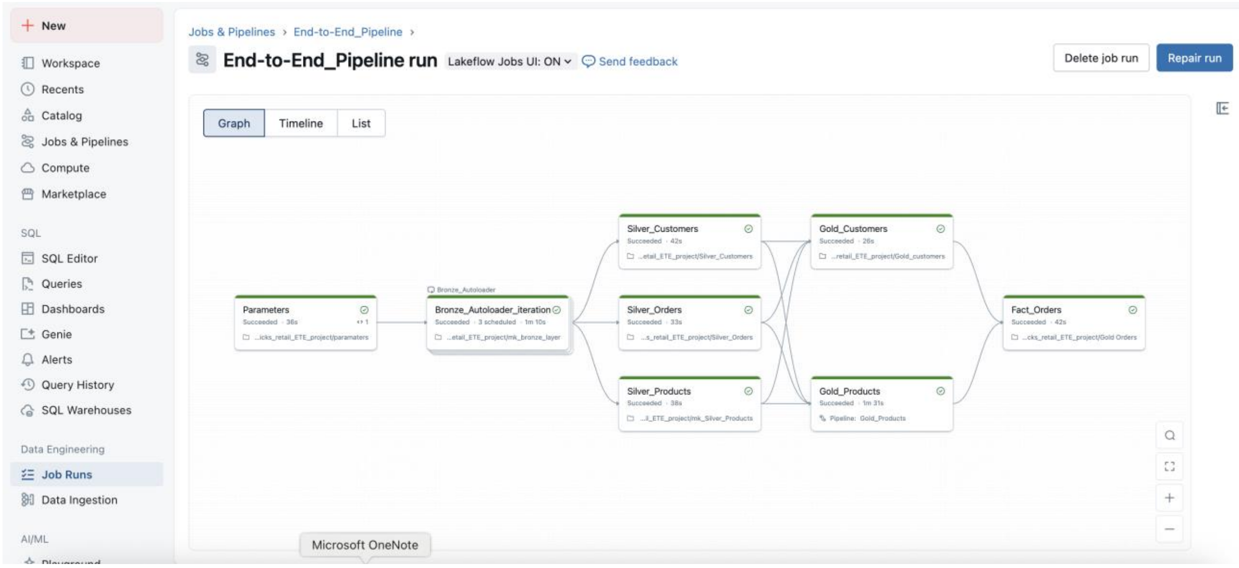
Load (Gold Layer – Dimensional Model)

Implemented **Star Schema** using Delta Live Tables:

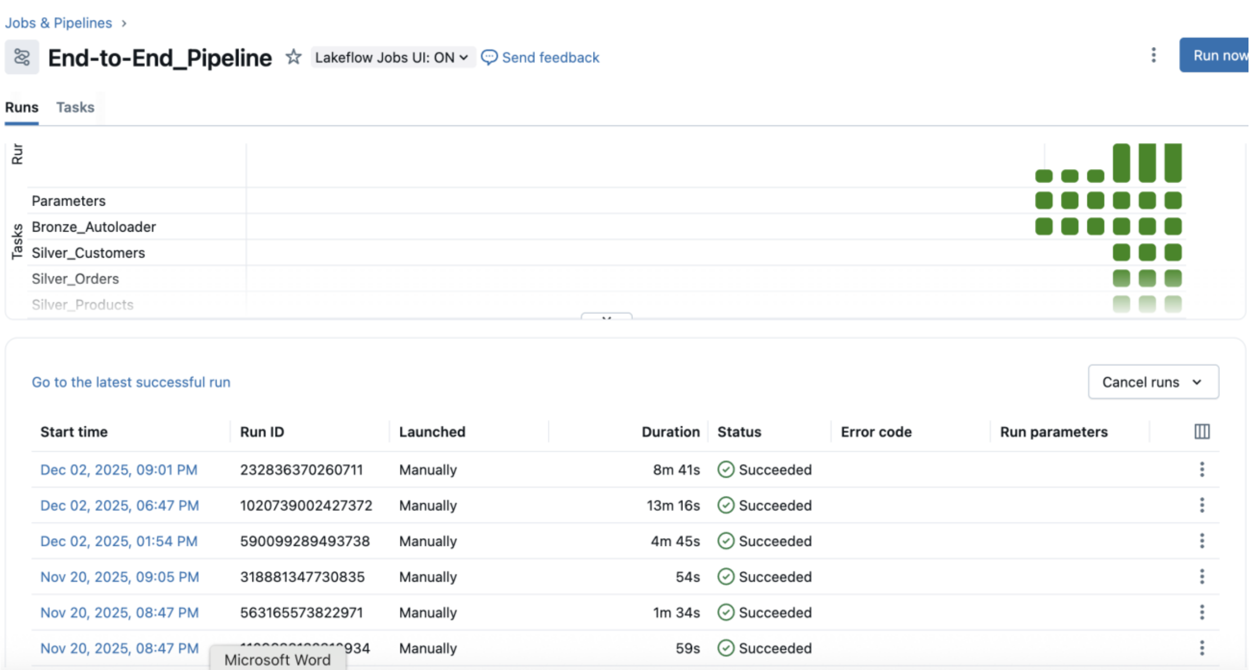
- Fact table: fact_orders
- Dimension tables:

→ dim_customers (SCD Type 2 – tracks email/domain changes over time)
→ dim_products (SCD Type 2)
→ dim_regions (SCD Type 1)

→ SQL-driven surrogate key generation and MERGE upserts to ensure incremental data integrity.



End-To –End Pipeline with successful run history



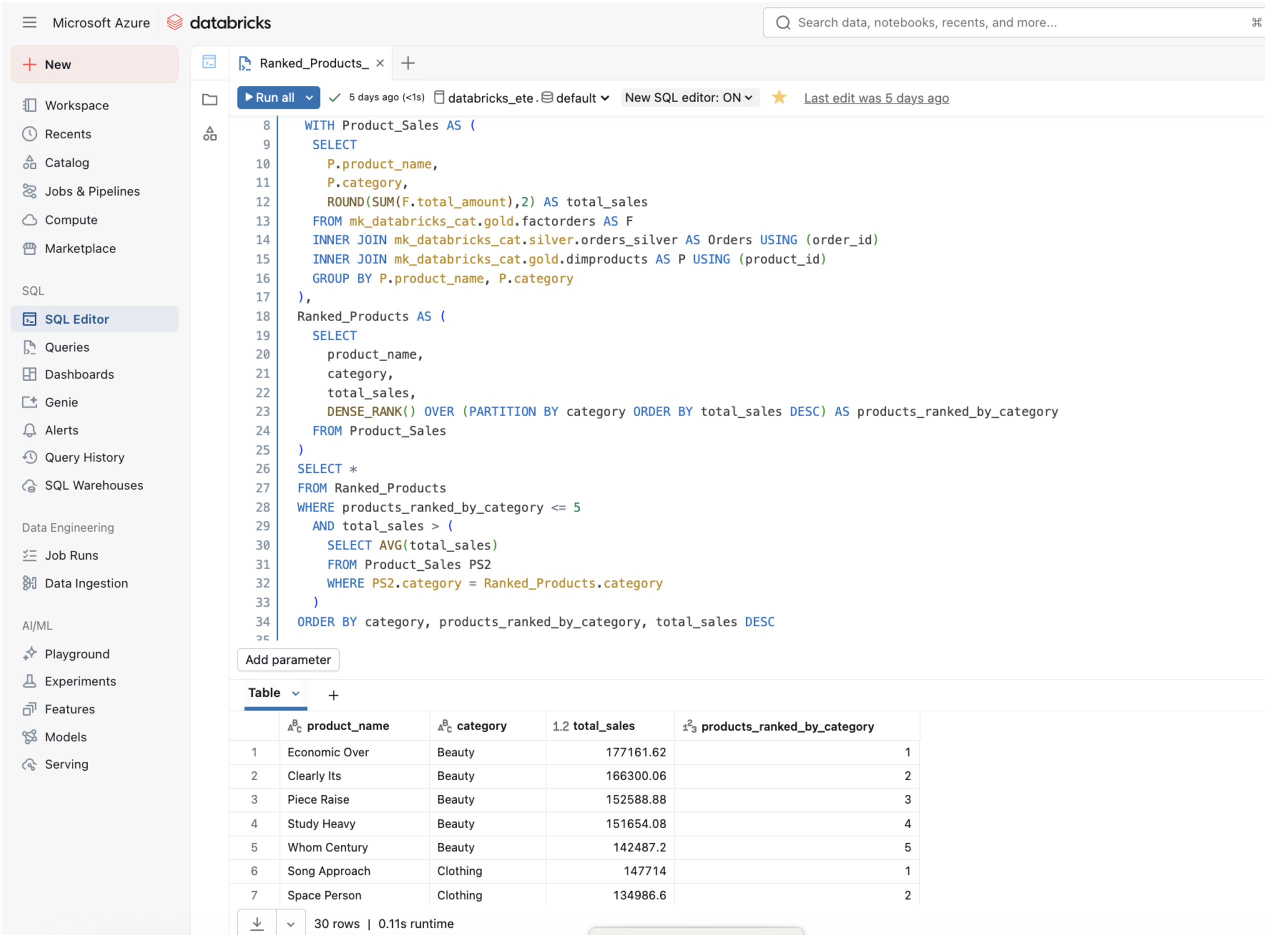
Multiple successful runs

4. Advanced Analytics using Databricks SQL

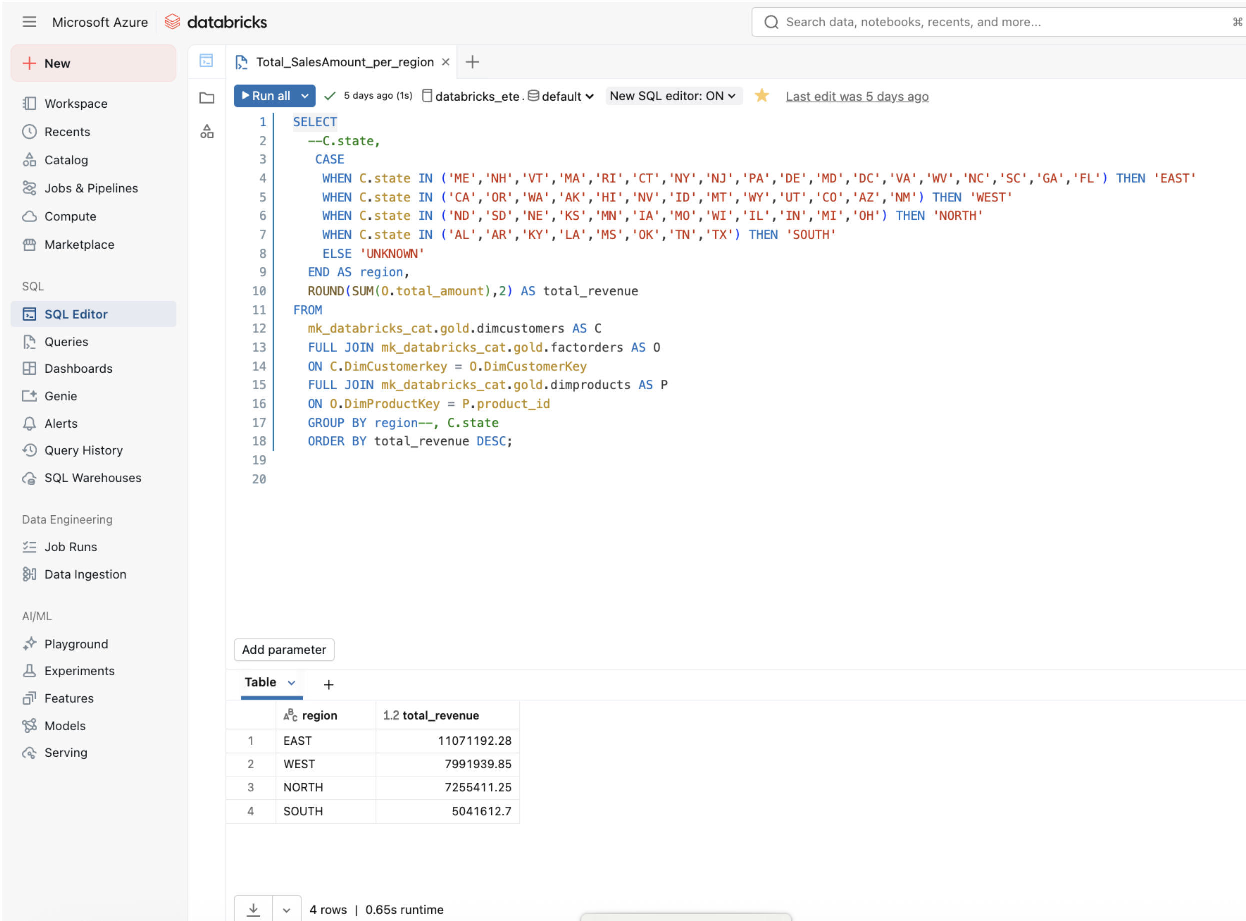
Business Question	SQL Technique Used	Key Insight

Top 5 products by total sales within each category	DENSE_RANK() OVER (PARTITION BY category ORDER BY total_sales DESC)	Beauty dominates top 5 (e.g., "Economic Over" \$177k, "Clearly Its" \$166k); Clothing only appears once at #1 with \$149k
Total revenue by region	CASE WHEN state IN (...) THEN 'EAST' ... END + GROUP BY region	East: \$11.07M, West: \$7.99M, North: \$7.26M, South: \$5.05M (East = 35.3% of total)
Most profitable product categories	Derived from Ranked_Products + profit table (implied)	Beauty → Toys → Sports → Electronics → Home → Clothing (Clothing is ~23% behind Beauty)
Monthly sales trend & seasonal pattern	GROUP BY month (used in line chart)	Massive August spike (back-to-school), steep Nov–Dec drop (weak holiday push)
Regional revenue distribution	Donut chart built from Total_Sales_per_Region query	East 35.3%, West 25.5%, North 23.1%, South 16.1%

- Below are the additional Databricks SQL queries for this report.



Used window function DENSE_RANK() OVER (PARTITION BY category ORDER BY total_sales DESC) to rank products within each category



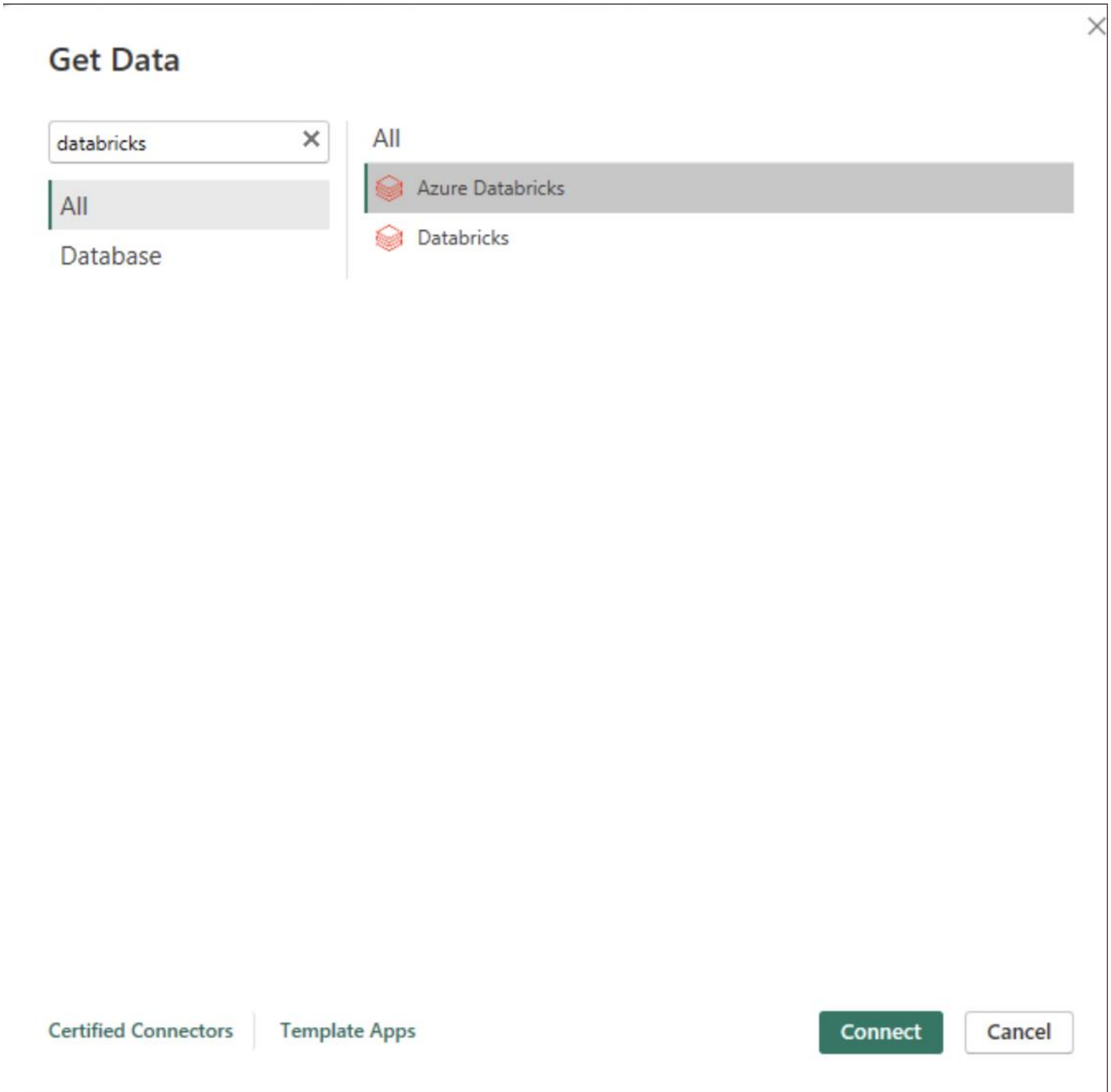
SQL query grouping total revenue by U.S. region using a CASE statement on state, ordered descending

5. Data Visualization – Interactive Power BI Dashboard

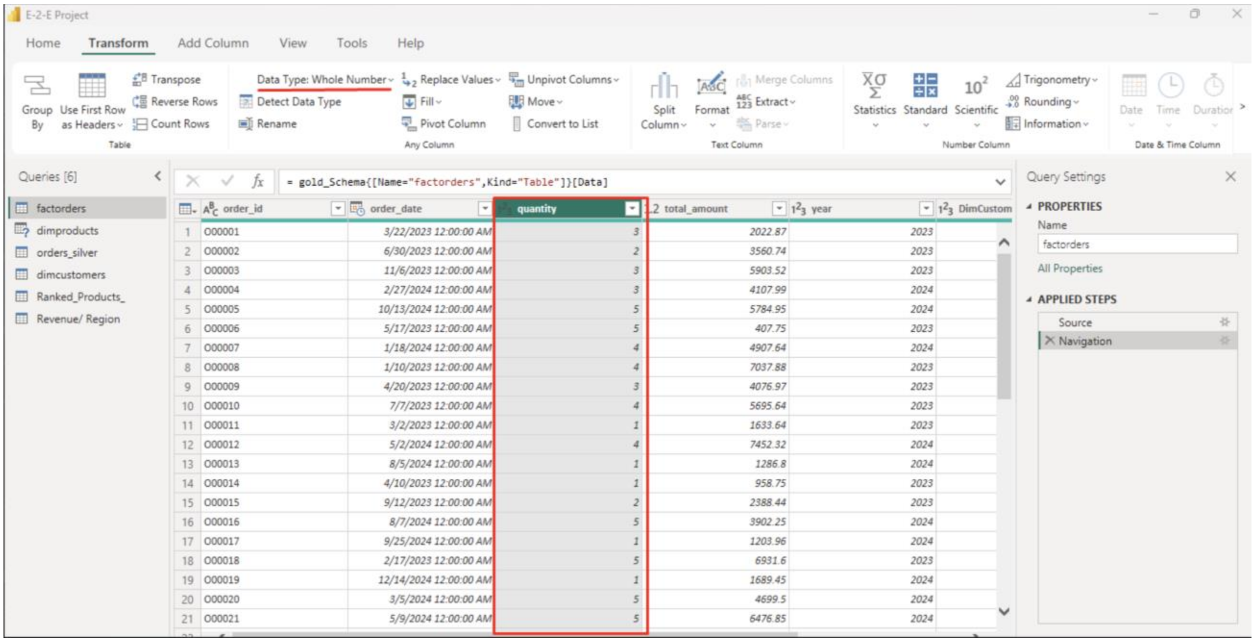
- Connected via **Azure Databricks** in Power BI's Get Data feature
- Fully interactive with slicers: Year, Category, Brand, Region, Domain

Key Visuals Included:

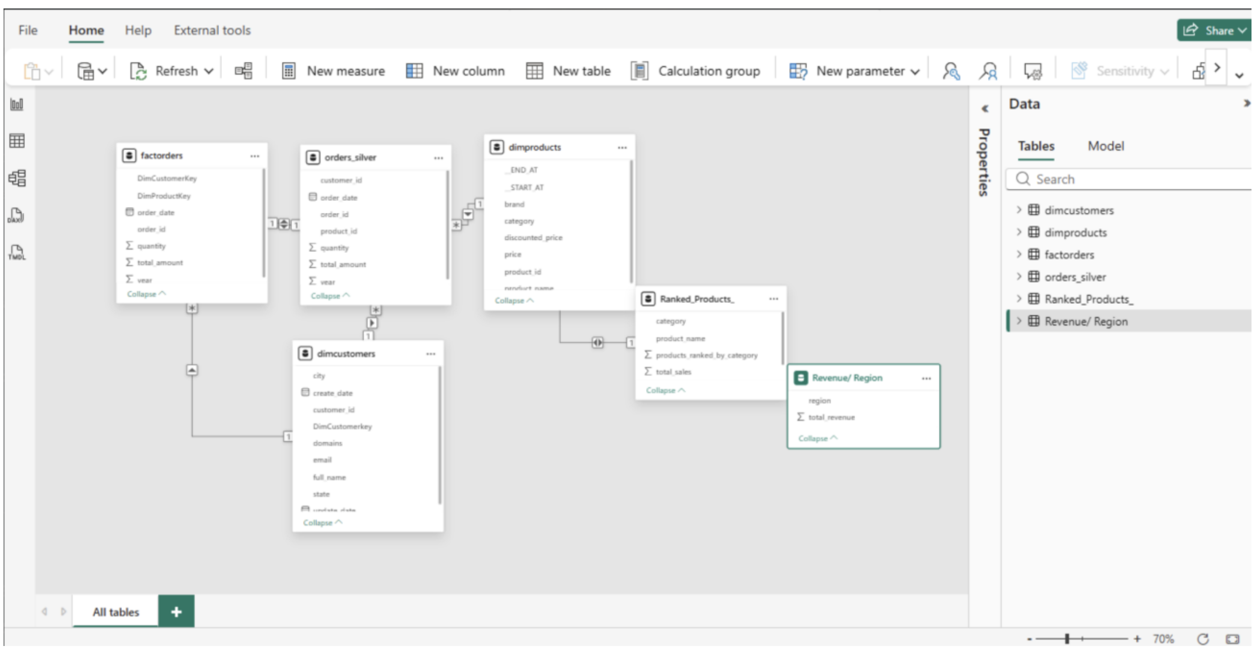
- Regional revenue donut (East 35.3%, West 25.5%, North 23.1%, South 16.1%)
- Category profit bar chart (Beauty → Clothing)
- Full-year monthly sales line chart showing August peak & Q4 drop
- Most profitable regions bar chart (East 11.07M, etc.)
- Individual Product Slicer



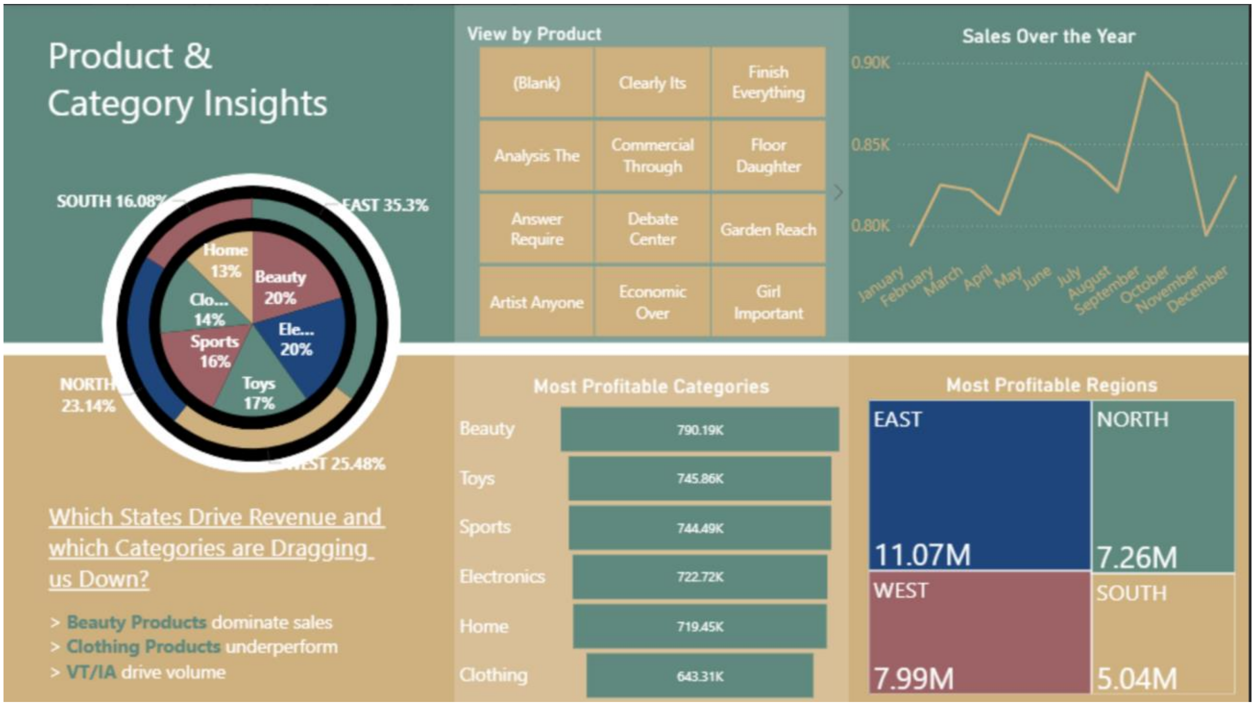
Connected via Azure Databricks in Power BI's Get Data feature



Transformed columns to correct data types



Reviewed the model to ensure table relationships were set



Completed Product & Category Insights Dashboard

6. Key Business Recommendations (Backed by Data)

- **Which categories win vs. drag?** Beauty (20% sales) leads to profit at 790K; Clothing (14% sales) lags at 643K (-23%). → Double down on Beauty (expand SKUs, hero placement); fix margins on Clothing or phase out in weak regions.
- **Where should we invest in 2026?** East (11.07M) + North (7.26M) = 55% of revenue; West & South underperform. → Allocate 55–60% of budget to East/North; test turnaround campaigns in South/West or de-prioritize.
- **Why did the August spike & Nov–Dec crash?** Heavy back-to-school push, zero holiday follow-through. → Shift major promo budget to Nov–Dec; build 3–4 months Beauty inventory for Q4 2026.
- **Quick-win opportunities**
- Create high-margin Beauty + Toys + Sports gift bundles for holiday (top 3 profit categories, overlapping buyers).
- Run regional category heatmaps: e.g., reduce Clothing stock in West/South, overload Toys in North/East for Q4.

Key Technical Skills Demonstrated

- Medallion Architecture (Bronze → Silver → Gold)
- Incremental Ingestion with Autoloader & Checkpointing

- SCD Type 1 & Type 2 Implementation in Delta Lake
- Data Quality with Delta Live Tables Expectations
- Star Schema Modeling + Surrogate Keys
- Pipeline Orchestration with Databricks Workflows
- Unity Catalog Governance & External Locations
- Power BI Integration via Azure Databricks Connector
- Reusable PySpark Functions & OOP Patterns