Understanding Customer Behavior

Cohort Insights Powered by a Production-Ready ELT Pipeline

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Unlocking Customer Value:
Cohort-Based Insights from 2024

01

Data:

- Jan-Dec 2024
- 200 customers
- 1.000 orders

02

Research Questions:

- How quickly do customers repurchase?
- How does retention differ across cohorts?
- How strong are repeat-purchase funnels?
- How have cohort sizes changed over time?

Disclaimer
Data Context & Limitations

01 Datascope:

- customer first purchases fall within Jan–Jun 2024 → only six cohorts
- sample too small to infer robust causal patterns

02 Limitations:

- we do **not** know the business model, industry, or seasonality patterns
- we do **not** know the marketing mix, budget, or campaign history

03 Interpretation:

- findings should be viewed as **directional**, not definitive
- recommendations are **hypotheses** for further investigation
- additional data would be needed for strategic decisions

ELT Data Stack:
From Cloud SQL Extraction to Databricks Transformation

Extract

raw data from Cloud SQL

Load

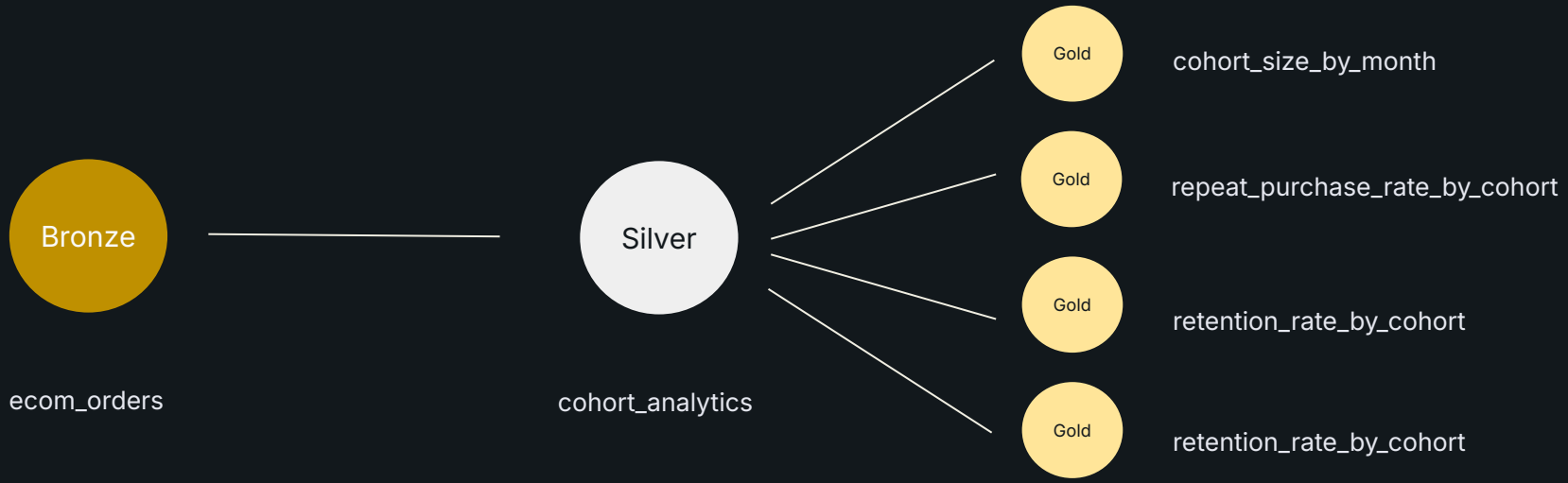
directly into Databricks via Fivetran

Transform

entirely inside the Lakehouse (SQL + Delta)

Medallion Architecture

Structured Data Layers ensure Analysis Quality and Reproducibility



Medallion Architecture

Silver

```sql
-- Step 1: Calculate the First Purchase Date
WITH first_purchases AS (
  SELECT
    customer_id,
    MIN(order_date) AS first_purchase_date,
    COUNT(*) AS total_orders
  FROM workspace.bigquery_db_cohort_db.bronze_ecom_orders
  GROUP BY customer_id
),

-- Step 2: Calculate the Second Purchase Date
second_purchases AS (
  SELECT
    eo.customer_id,
    MIN(eo.order_date) AS second_purchase_date
  FROM workspace.bigquery_db_cohort_db.bronze_ecom_orders AS eo
  JOIN first_purchases fp ON eo.customer_id = fp.customer_id
  WHERE eo.order_date > fp.first_purchase_date
  GROUP BY eo.customer_id
)

-- Step 3: Combine the Results and Calculate the Days Between Purchases
SELECT
  fp.customer_id,
  first_purchase_date,
  total_orders,
  second_purchase_date,
  DATEDIFF(second_purchase_date, first_purchase_date) AS days_between_first_and_second
FROM first_purchases AS fp
LEFT JOIN second_purchases AS sp ON fp.customer_id = sp.customer_id
```

- Derive 1st and 2nd purchase dates
- Calculate days between purchases
- Count total customer orders

Medallion Architecture

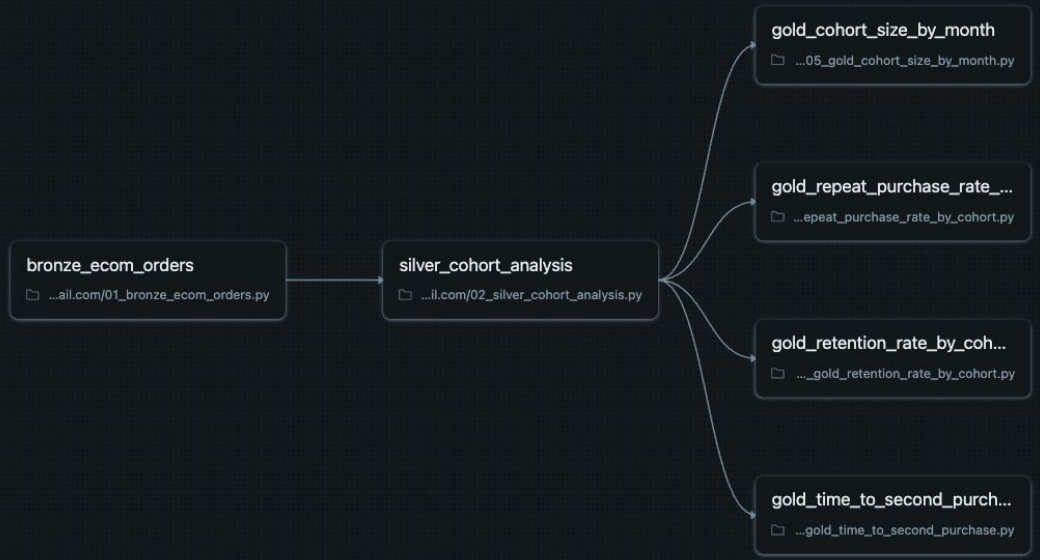
Gold

```sql
create or replace table workspace.bigquery_db_cohort_db.gold_retention_rate_by_cohort as

-- 1) Compute the month difference and cohort month
WITH customer_differences AS (
    SELECT
        customer_id,
        DATE_TRUNC('month', first_purchase_date) AS cohort_month,
        first_purchase_date,
        second_purchase_date,
        FLOOR(
            MONTHS_BETWEEN(second_purchase_date, first_purchase_date)
        ) AS month_diff
    FROM workspace.bigquery_db_cohort_db.silver_cohort_analysis
)

-- 2) Aggregate cumulative retention rates
SELECT
    DATE_FORMAT(cohort_month, 'yyyy-MM') AS cohort_month,
    COUNT(*) AS num_customers,
    ROUND(100.0 * SUM(CASE WHEN month_diff <= 1 THEN 1 END) / COUNT(*)) AS retention_rate_1m,
    ROUND(100.0 * SUM(CASE WHEN month_diff <= 2 THEN 1 END) / COUNT(*)) AS retention_rate_2m,
    ROUND(100.0 * SUM(CASE WHEN month_diff <= 3 THEN 1 END) / COUNT(*)) AS retention_rate_3m
FROM customer_differences
GROUP BY cohort_month
ORDER BY cohort_month;
```

- Calculate month difference:
  1st and 2nd purchase
- Compute cohort_month
- Aggregate cumulative retention rates

From Concept to Production: Automated Medallion Pipeline

SQL-based modeling operationalized with PySpark and Databricks Jobs

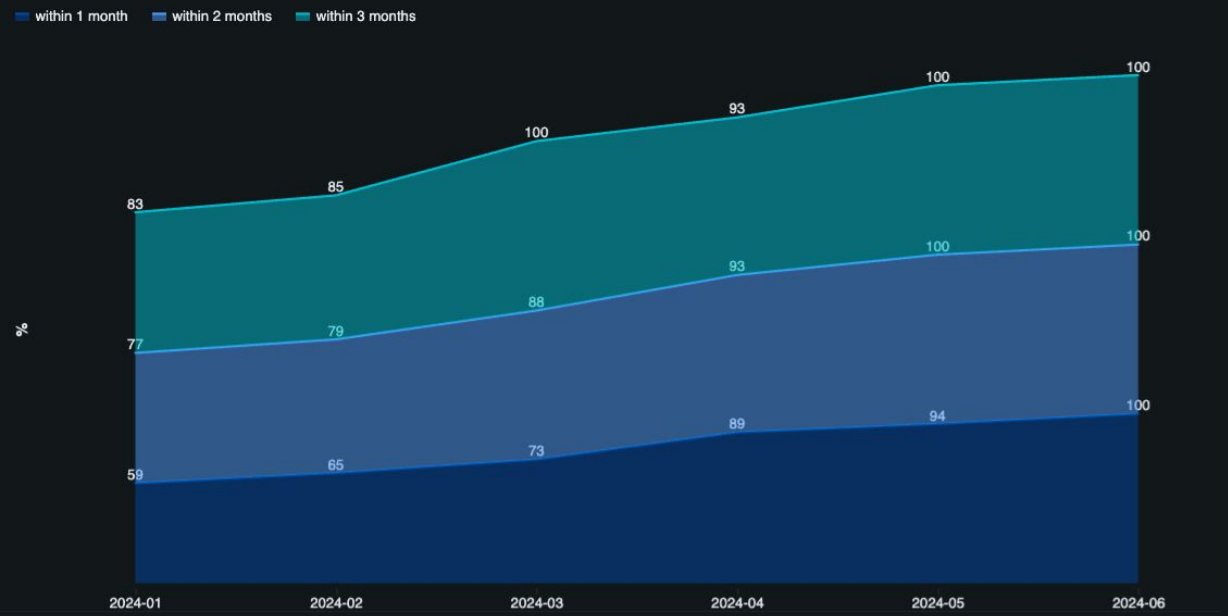


- PySpark notebooks implement each Medallion layer
- Transformations materialized as Delta tables
- Dependencies orchestrated via Databricks Jobs
- Pipeline designed for idempotent, repeatable execution

Dashboard Overview

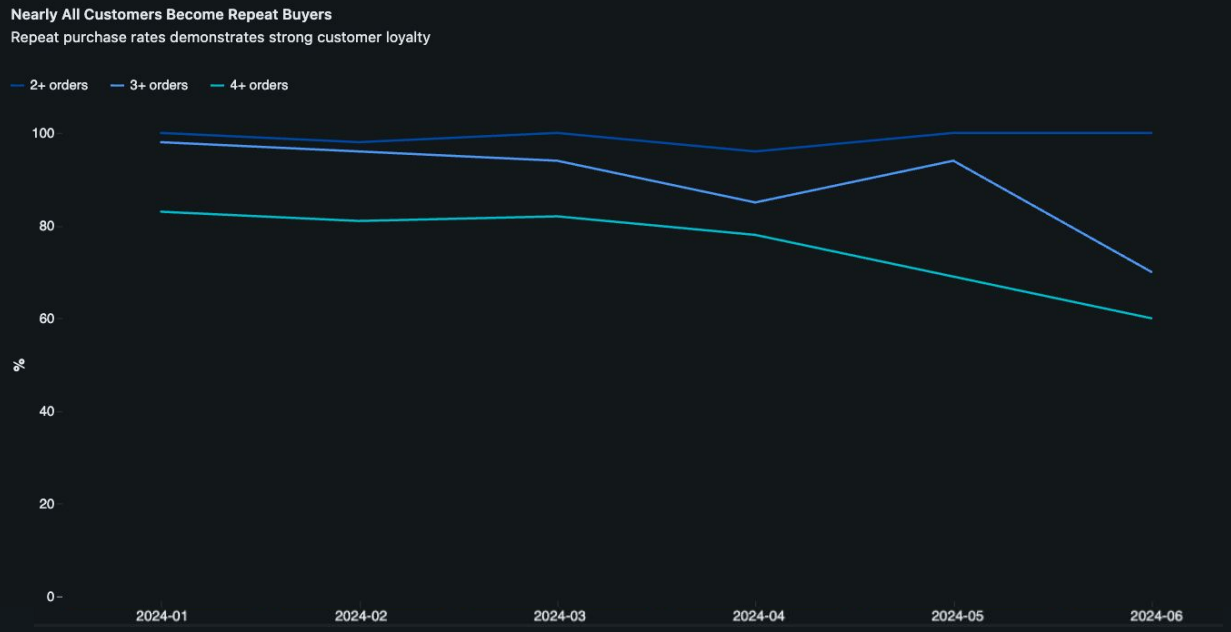
Retention Remains Strong Across Cohorts, Improving In Recent Months

Newer cohorts exhibit consistently stronger early-stage retention



- **1-month retention:**
  59% → 100%
- **2-month retention:**
  rises steadily across cohorts
- **3-month retention:**
  stabilizes around ~90%
  in later months

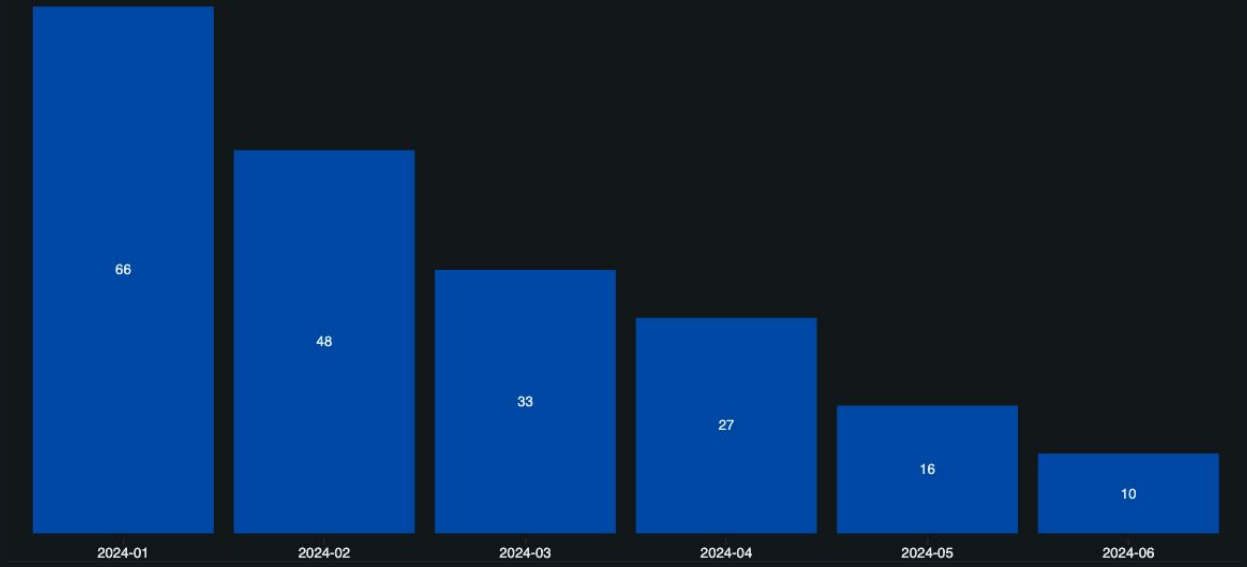
Nearly All Customers Become Repeat Buyers
Repeat purchase rates demonstrates strong customer loyalty



- **2+ orders:**
  ~100% across all cohorts
- **3+ orders:**
  85–96% for early cohorts; slight dip for June
- **4+ orders:**
  strong, but decreasing in latest cohort

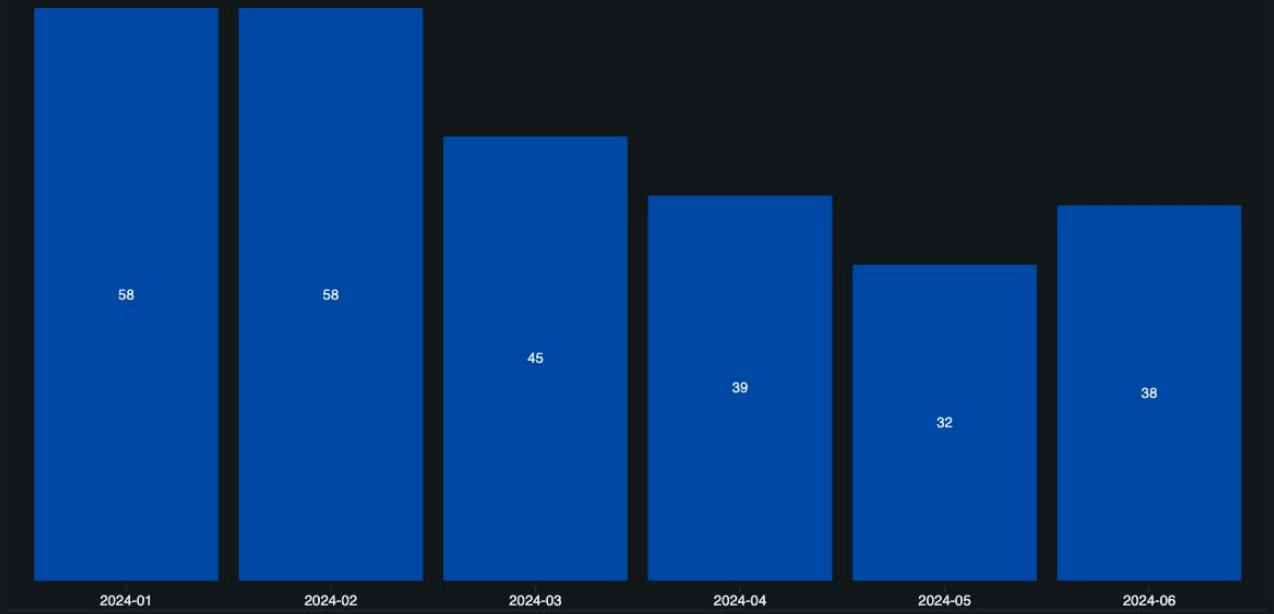
New Customer Acquisition Fell Steadily Over The Period

Cohort sizes declined by 85% from Jan. to Jun.



Repurchase Cycle Is Shortening Across Cohorts

Average days to second purchase declined from ~58 to ~38 days



Conclusions & Recommendations

1 — Retention appears strong

- Later cohorts show higher early-stage retention
- This may indicate improved onboarding, acquisition quality, or product-market fit

Next step:
Review whether internal process changes occurred during the period

2 — Drastically declining acquisition volume

- This might reflect seasonality, marketing shifts, or one-time events
- With only six data points, no trend can be confirmed

Next step:
Investigate channel performance, seasonality, and marketing spend

3 — Repurchase cycles seem to be shortening

- Could reflect better customer engagement or improved product experience
- But later cohorts have less elapsed time, so estimates may be biased downward

Next step:
Validate with larger time range and longer follow-up period

4 — Opportunity to strengthen analytics foundations

- Potential long-term enhancements:
    - LTV models
    - Churn prediction
    - Segmentation (behavioral cohorts)

Thank you

Full project documentation on:
github.com/roberto-pera/databricks-elt-cohort-analysis