Project Title

Supermart Profit Prediction & Retail Business Analytics System

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Business Problem

Retail businesses face challenges in predicting profit due to fluctuating sales, discount strategies, seasonal demand, and product-level variations. Business teams need a reliable system to **analyze historical performance** and **predict future profitability** before making pricing or promotional decisions.

Project Objective

The objectives of this project were:

- To analyze historical supermarket sales data
- To understand the relationship between sales, discounts, and profit
- To build a machine learning model for profit prediction
- To deploy an interactive application for real-time business decision support
- To demonstrate the use of **Excel, SQL, Python, and Machine Learning** in a single end-to-end project

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Dataset Overview

The dataset contains historical grocery sales transactions with attributes such as:

- Order details (Order ID, Customer Name)
- Product information (Category, Sub-category)
- Location details (City, Region, State)
- Financial metrics (Sales, Discount, Profit)
- Time-related information (Order Date)

This dataset represents a realistic retail environment suitable for business analytics and predictive modeling.

TOOLS & TECHNOLOGIES USED

- **Excel** – Initial data understanding & validation
- **SQL** – Structured querying & business-level analysis
- **Python** – Data cleaning, EDA, feature engineering
- **Machine Learning (Scikit-learn)** – Model development
- **Streamlit** – Model deployment & dashboard creation

□ Step 1: Excel Analysis (WHY & HOW)

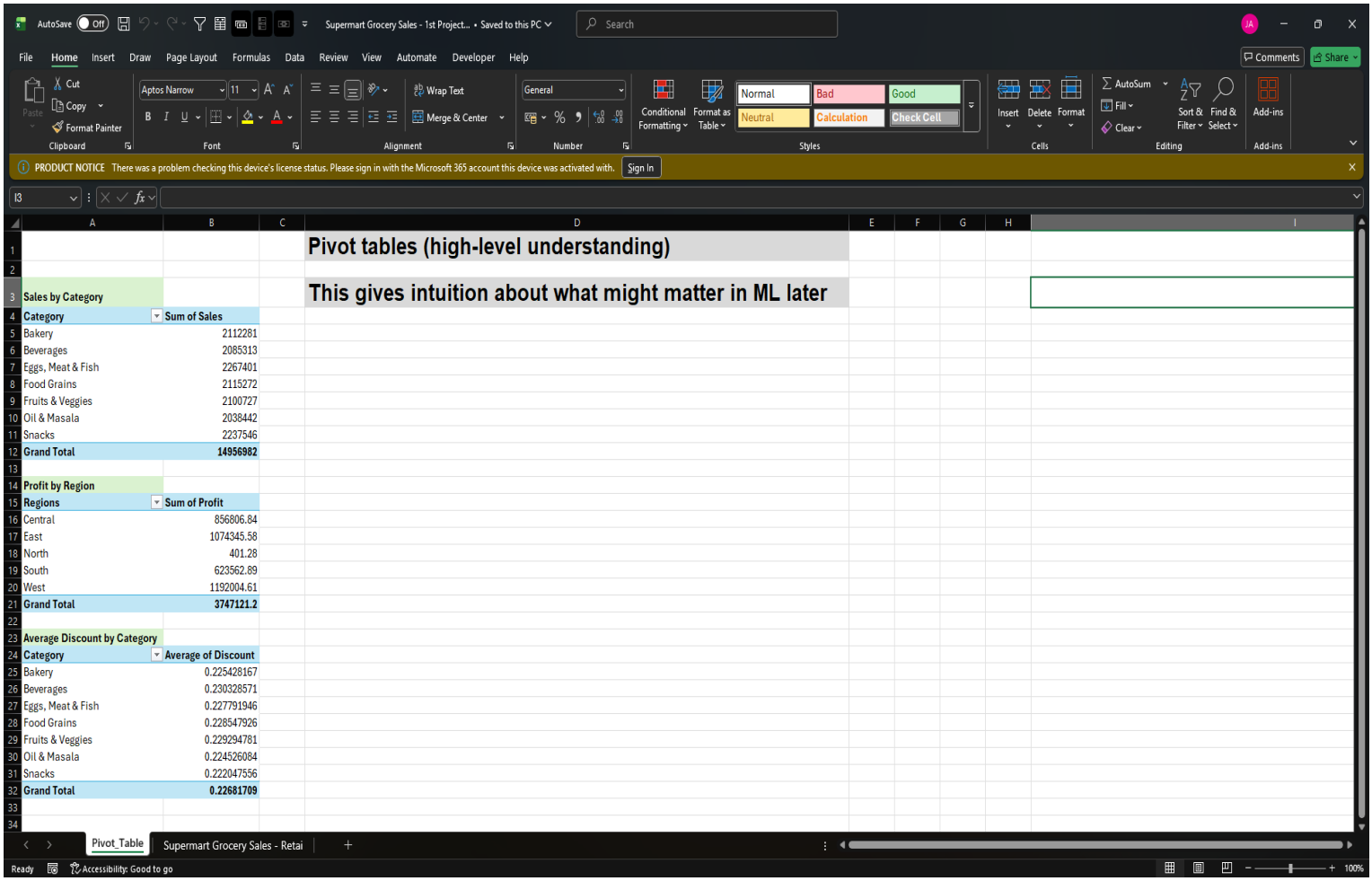
□ Why Excel was used

Excel was used as the **first-level analysis tool** to quickly understand the data before moving to advanced tools.

□ What was done in Excel

- Reviewed raw data structure and column meanings
- Checked for missing values and incorrect data types
- Identified outliers in Sales, Discount, and Profit
- Created basic pivot tables:
  - Category-wise sales and profit
  - Region-wise performance
- Used charts to visually understand:
  - Sales vs Profit trends
  - Discount impact on profit

□ **Outcome:**
Excel helped validate data quality and provided initial business insights that guided further analysis in SQL and Python.



□ Step 2: SQL Analysis (WHY & HOW)

□ Why SQL was used

SQL was used to perform **structured, business-driven analysis** similar to how data is analyzed in real organizations using databases.

□ What was done using SQL

- Queried total sales and profit by:
  - Category
  - Sub-category
  - Region
- Identified top-performing and low-performing products
- Analyzed discount impact using grouped aggregations
- Validated business KPIs such as:
  - Average discount per region
  - Profit contribution by category

□ **Example business questions answered via SQL:**

- Which category generates the highest profit?
- Which region is most sensitive to discounts?
- How does profit vary across different product segments?

□ **Outcome:**
SQL helped transform raw data into **business-ready insights** and ensured the analysis aligned with real-world reporting practices.

□ Step 3: Data Cleaning & Preprocessing (Python)

Python was used for deeper data preparation:

- Cleaned and standardized column names
- Converted numerical and date fields to proper formats
- Removed irrelevant columns for modeling
- Handled encoding of categorical variables
- Prepared a clean dataset suitable for machine learning

□ Step 4: Exploratory Data Analysis (EDA)

EDA was performed using Python libraries:

- Analyzed distributions of sales, profit, and discount
- Studied relationships such as:
  - Discount vs Profit
  - Category vs Profit

- Identified seasonal patterns using year and month

This step confirmed many insights initially observed in Excel and SQL.

□ Step 5: Feature Engineering

Additional features were created to enhance model learning:

- Year, Month, Quarter
- Weekend indicator
- One-hot encoding for categorical variables
- Numeric-only feature selection for ML compatibility

□ Step 6: Machine Learning Modeling

Baseline Model: Linear Regression

- Used to establish a baseline performance
- Provided interpretability of linear relationships

Advanced Model: Random Forest Regressor

- Captured non-linear patterns
- Improved handling of complex feature interactions
- Provided better business-level insights

Models were evaluated using:

- Mean Absolute Error (MAE)
- R^2 Score

□ Step 7: Model Deployment using Streamlit

The trained Random Forest model was deployed using Streamlit Cloud:

- Users can input order details
- Real-time profit predictions are generated
- Business warnings and insights are displayed
- The app converts ML output into actionable insights

This step transformed the analysis into a **production-style business application**.

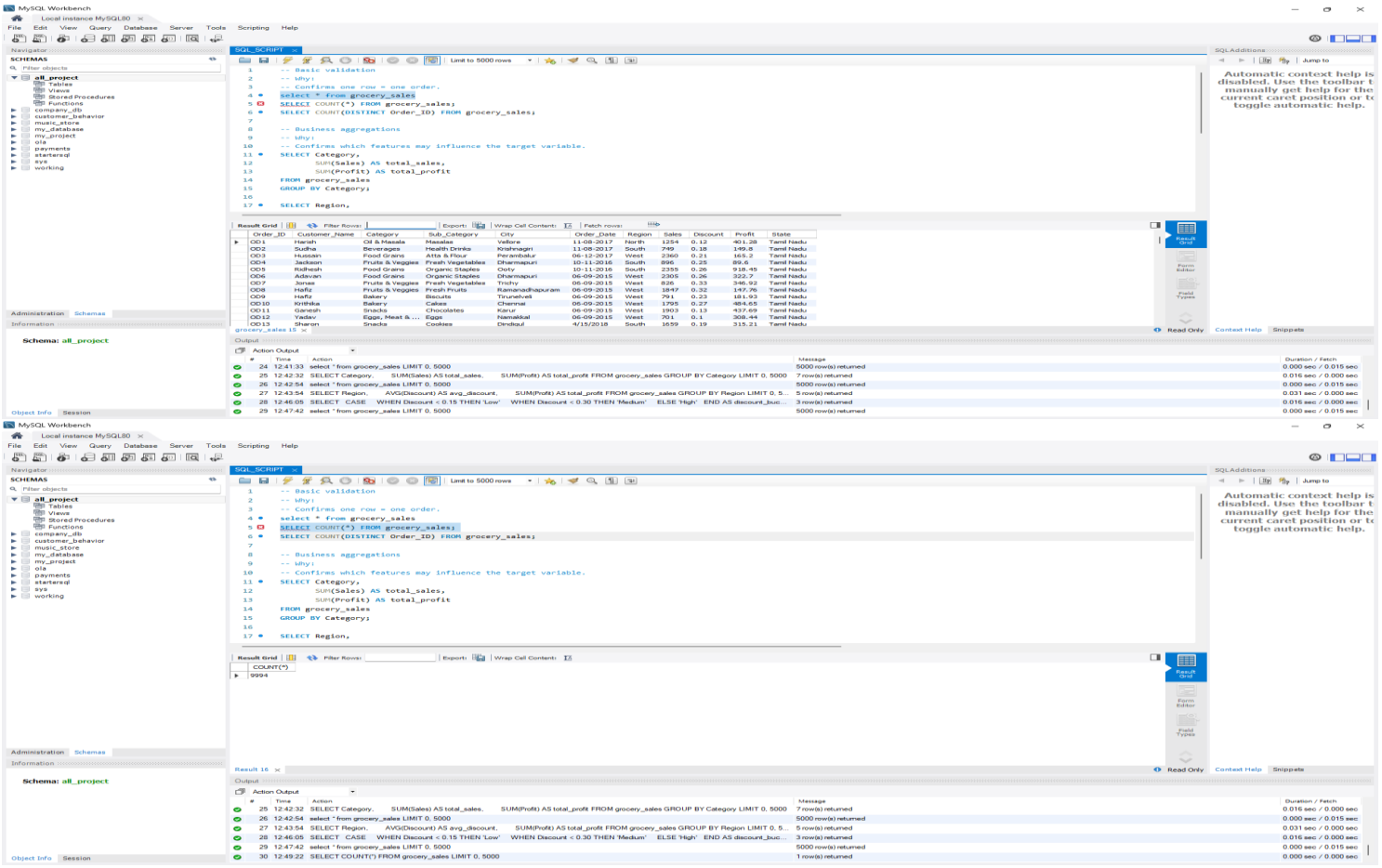
□ Business Impact & Insights

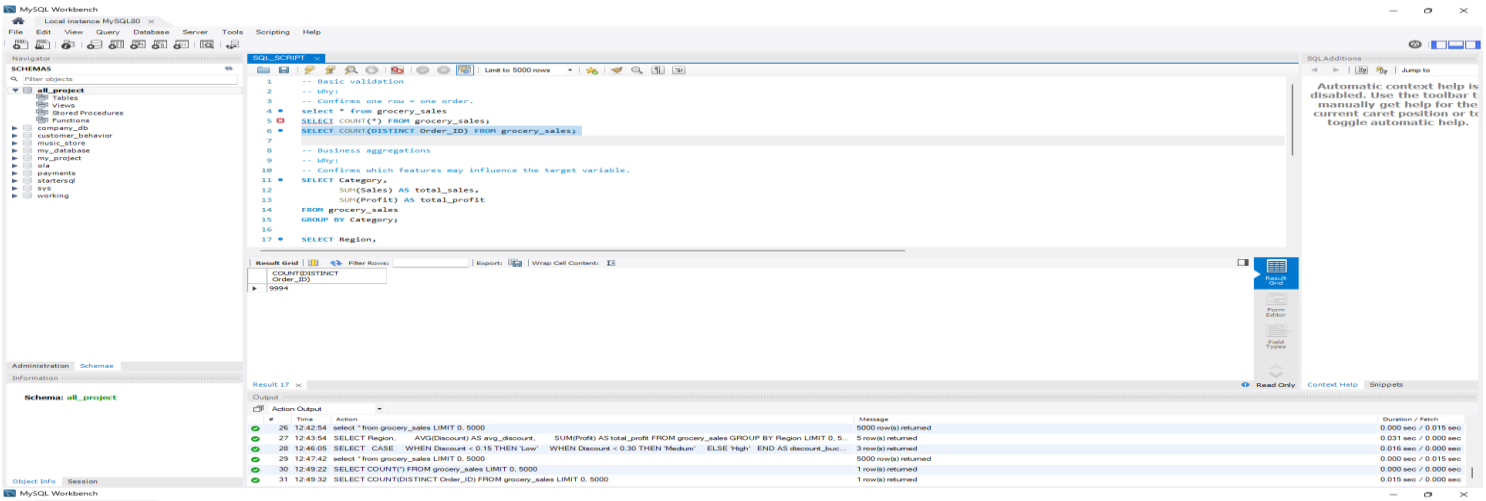
- High discounts negatively impact profitability
- Certain categories consistently perform better
- Profit prediction supports pricing and promotion decisions
- Scenario testing reduces financial risk

□ Final Conclusion

This project demonstrates a complete retail analytics solution by combining Excel, SQL, Python, Machine Learning, and Streamlit deployment. Excel and SQL were used for initial data validation and business-level analysis, while Python enabled advanced analytics and modeling. The final deployed application allows stakeholders to predict profit in real time and make informed business decisions. This project reflects real-world data science workflows and highlights the importance of combining technical skills with business understanding.

SQl Results :



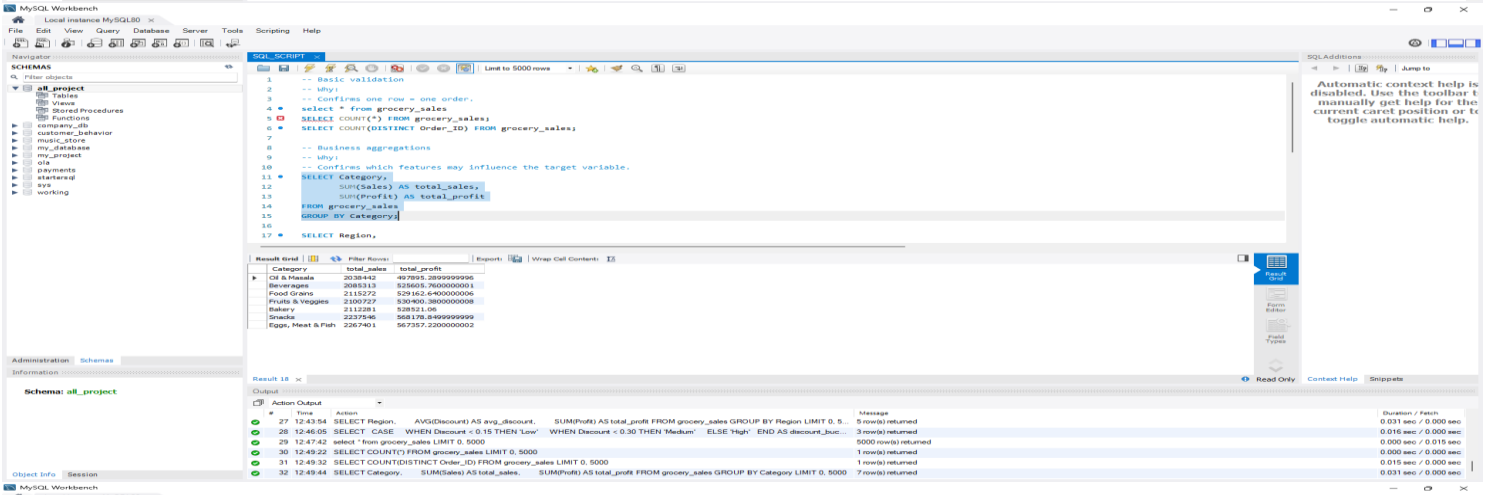


```
-- Basic validation
-- Why:
-- Confirms one row = one order.
select * from grocery_sales
SELECT COUNT(*) FROM grocery_sales;
SELECT COUNT(DISTINCT Order_ID) FROM grocery_sales;

-- Business aggregations
-- Why:
-- Confirms which features may influence the target variable.
SELECT Category,
       SUM(Sales) AS total_sales,
       SUM(Profit) AS total_profit
FROM grocery_sales
GROUP BY Category;

SELECT Region,
```

COUNT(DISTINCT Order_ID)
9994



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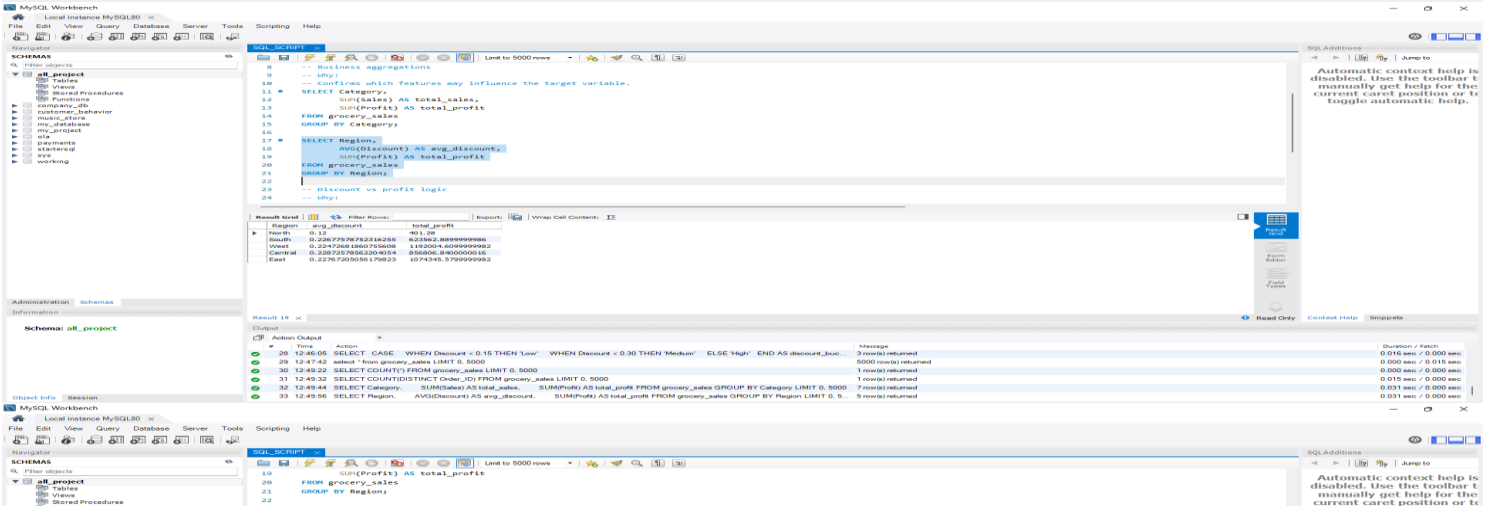
SELECT Region,
```

Category	total_sales	total_profit
Oil & Masala	2038442	497895.2899999996
Beverages	2085313	525605.7600000001
Food Grains	2115272	529162.6400000006
Fruits & Veggies	2100727	530400.3800000008
Bakery	2112281	528521.06
Snacks	2237546	568178.8499999999
Eggs, Meat & Fish	2267401	567357.2200000002

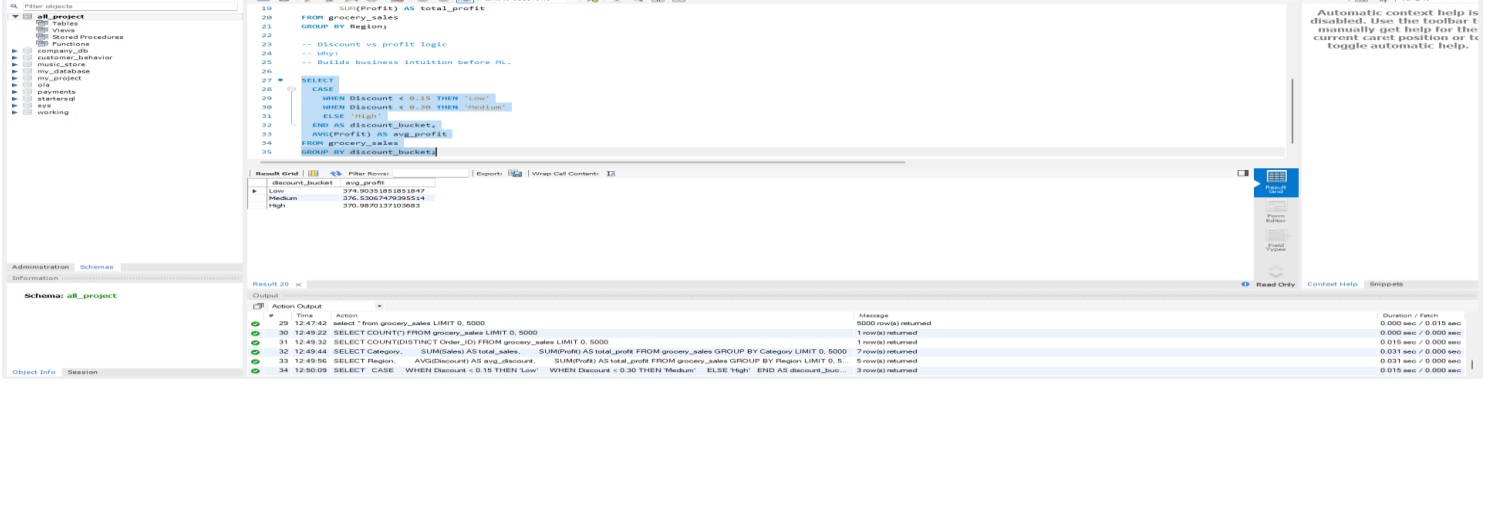


```
        -- Business aggregations
        -- Why:
        -- Confirms which features may influence the target variable.
        SELECT Category,
               SUM(Sales) AS total_sales,
               SUM(Profit) AS total_profit
        FROM grocery_sales
        GROUP BY Category;

        SELECT Region,
               AVG(Discount) AS avg_discount,
               SUM(Profit) AS total_profit
        FROM grocery_sales
        GROUP BY Region;

        -- Discount vs profit logic
        -- Why:
```

Region	avg_discount	total_profit
North	0.12	401.28
South	0.22677578752316255	623362.8899999986
West	0.22472681907556608	619204.4099999982
Central	0.22872578562204054	856806.8400000016
East	0.22767305161796323	617434.5799999982



```
               SUM(Profit) AS total_profit
        FROM grocery_sales
        GROUP BY Region;

        -- Discount vs profit logic
        -- Why:
        -- Builds business intuition before ML.

        SELECT
          CASE
            WHEN Discount < 0.15 THEN 'Low'
            WHEN Discount < 0.30 THEN 'Medium'
            ELSE 'High'
          END AS discount_bucket,
          AVG(Profit) AS avg_profit
        FROM grocery_sales
        GROUP BY discount_bucket;
```

discount_bucket	avg_profit
Low	374.90351851851847
Medium	376.5306747939551 4
High	370.98701371013683