Final Group Project

Data Science and Analytics Using GCP Cloud Computing Technologies

Group 21 (Team Members)

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Project URL - https://group21cloud.uc.r.appspot.com/

Development Details

- **Database**: MySQL on Google Cloud SQL
- **Framework**: Python Flask
- **Deployment**: Google App Engine
- **Region**: us-central1
- **Required Python Version**: 3.9
- **GitHub URL:** https://github.com/rohzzn/retailanalytics

Key Features

- User Authentication
- Interactive Dashboard
- Real-time Data Search
- ML-based Analytics
- Data Upload Capability

Source Data

- Sample Size: 400 households
- Time Period: 2018-2020
- Data Files: households.csv, products.csv, transactions.csv
- Total Records: ~85,000 transactions

1. ML Models Write-up

Linear Regression:
Linear Regression fits a linear relationship between input features and a continuous target variable. In retail, it can be used to predict Customer Lifetime Value (CLV) by using features like purchase frequency, average basket size, and household demographics. It provides an interpretable model, showing how each predictor impacts the predicted CLV.

Random Forest:
A Random Forest is an ensemble of decision trees that improves predictive performance and robustness. In retail, it can handle diverse data (both categorical and numerical), making it ideal for predicting churn or segmenting customers. It mitigates overfitting and often provides strong predictive accuracy.

Gradient Boosting:
Gradient Boosting builds models sequentially, each new model correcting errors from the previous. It's very effective for capturing complex patterns and interactions. In retail, gradient boosting can predict churn or CLV with high accuracy, adapting to subtle patterns in purchasing behavior, loyalty, and demographics.

Customer Lifetime Value (CLV) - How can we predict long-term revenue potential to prioritize high-value customers?

Rationale: Gradient Boosting is highly effective for predictive modeling tasks like CLV due to its ability to handle complex relationships and interactions between features. It often provides superior performance compared to simpler models like Linear Regression, making it ideal for accurately predicting long-term revenue potential.

Implementation Steps:

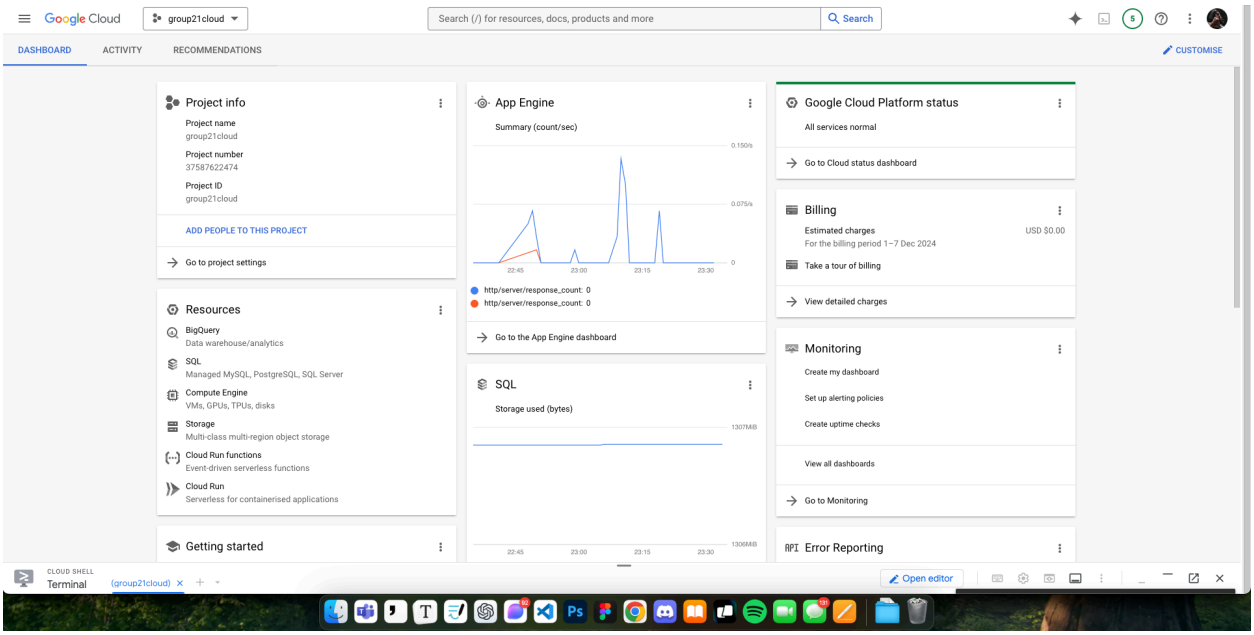
1. **Feature Engineering**: Use features such as total baskets, total spend, average spend per trip, days since last purchase, household size, presence of children, income range etc

2. **Model Training**: Split the data into training and testing sets. Train a Gradient Boosting model on the training data**.** Evaluate model performance using metrics like R-squared and Mean Absolute Error (MAE).

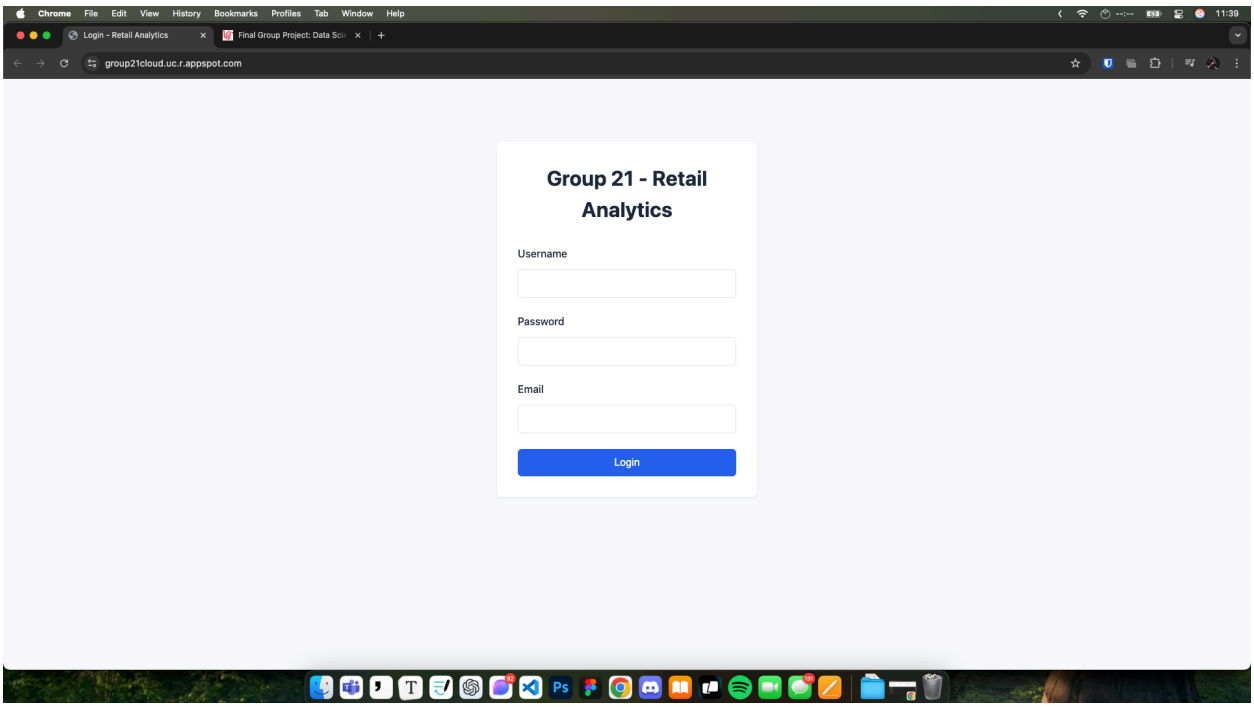
3. **Integration with Dashboard**: Display predicted CLV for each household. Highlight high-value customers for targeted marketing.

2. Web Server Setup

We launched a Flask application hosted on GCP App Engine. Users can access a login page with fields for username, password, and email.

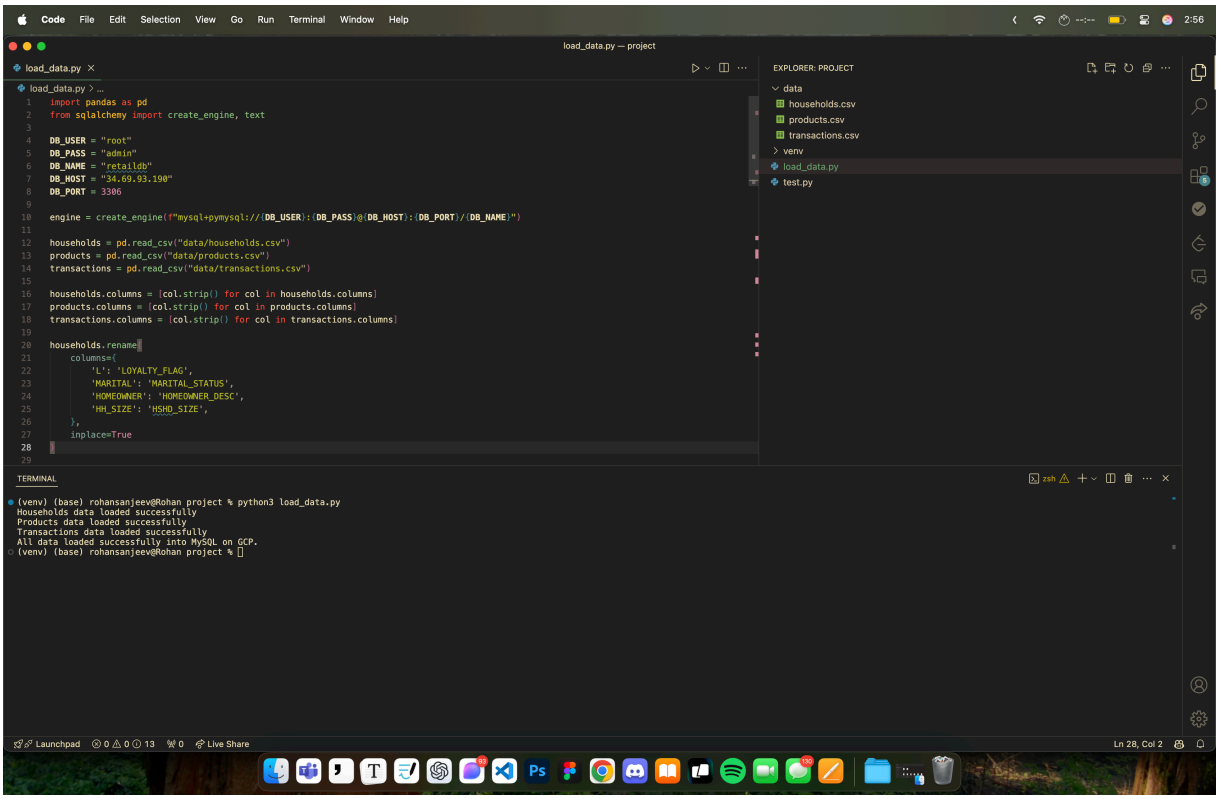


Login Page

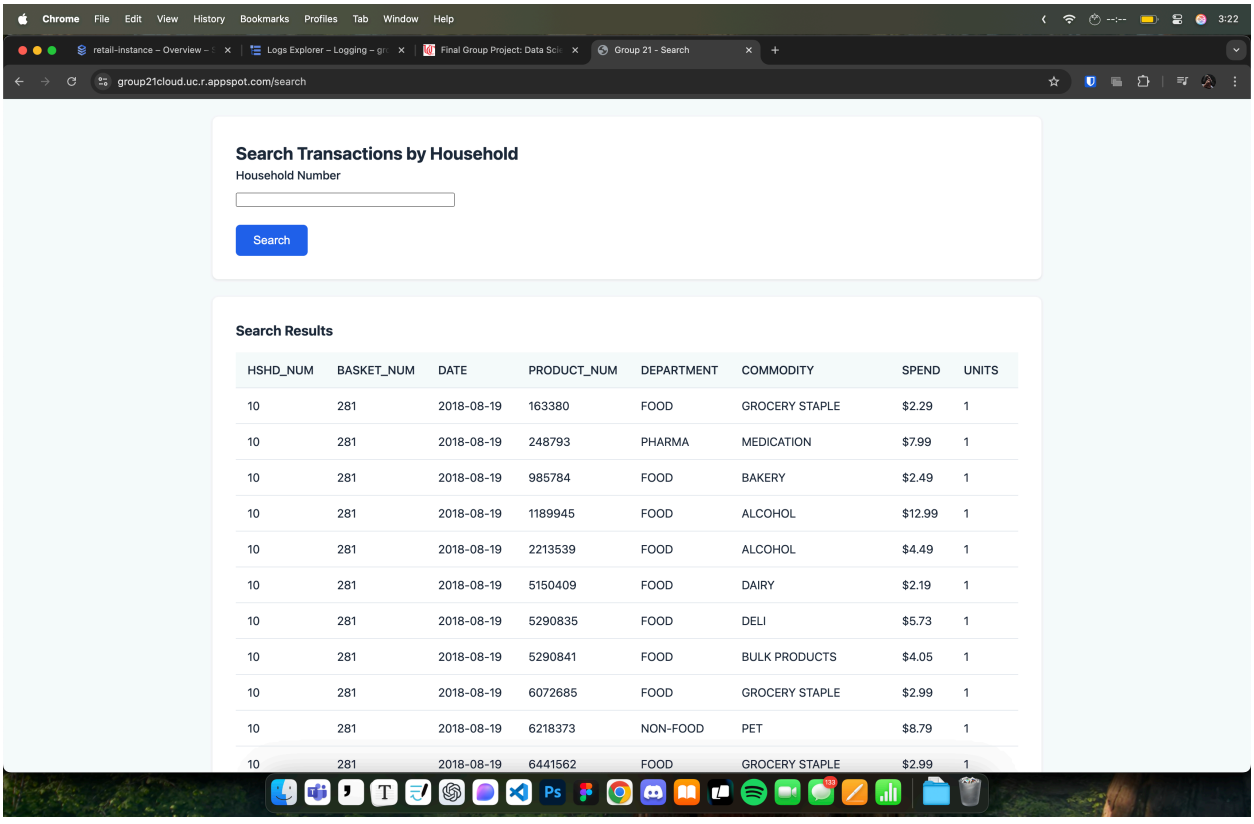


3. Datastore and Data Loading

Created database in GCP and loaded the given data.



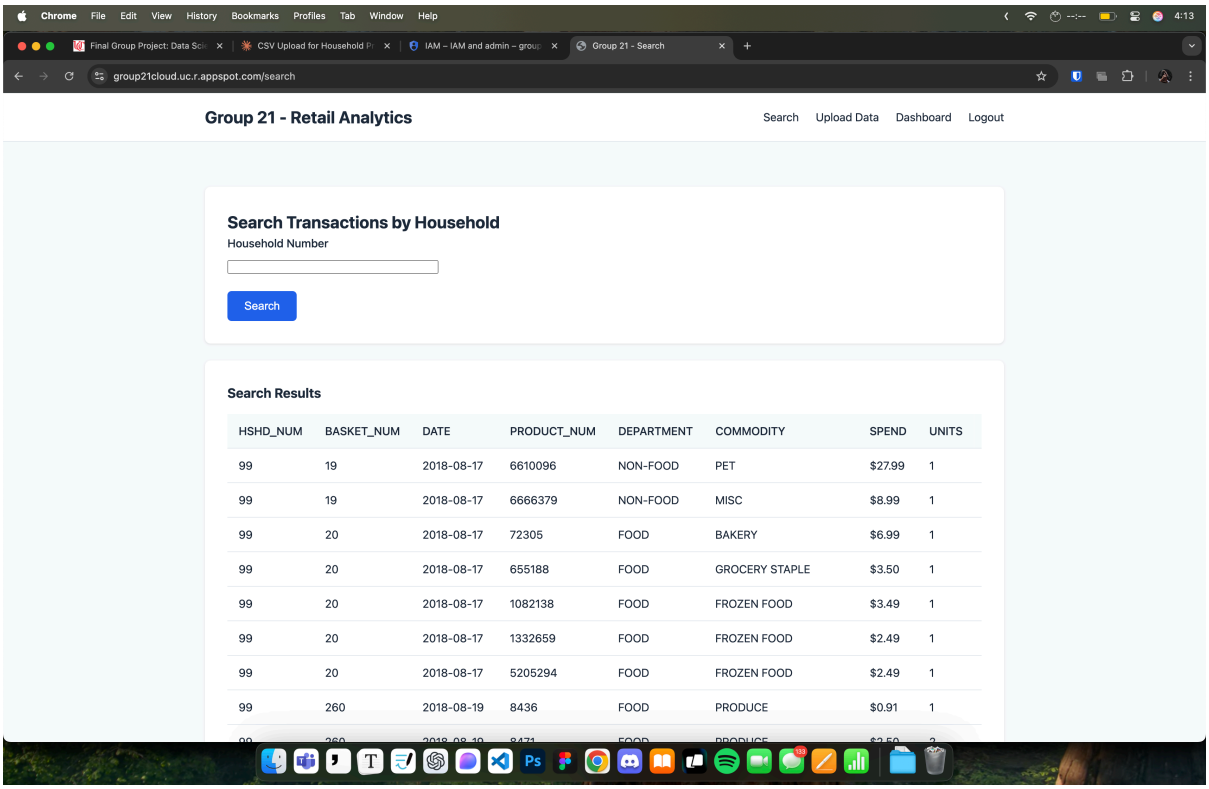
Here a display page for a Sample Data Pull for **HSHD_NUM #10**,



HSHD_NUM	BASKET_NUM	DATE	PRODUCT_NUM	DEPARTMENT	COMMODITY	SPEND	UNITS
10	281	2018-08-19	163380	FOOD	GROCERY STAPLE	$2.29	1
10	281	2018-08-19	248793	PHARMA	MEDICATION	$7.99	1
10	281	2018-08-19	985784	FOOD	BAKERY	$2.49	1
10	281	2018-08-19	1189945	FOOD	ALCOHOL	$12.99	1
10	281	2018-08-19	2213539	FOOD	ALCOHOL	$4.49	1
10	281	2018-08-19	5150409	FOOD	DAIRY	$2.19	1
10	281	2018-08-19	5290835	FOOD	DELI	$5.73	1
10	281	2018-08-19	5290841	FOOD	BULK PRODUCTS	$4.05	1
10	281	2018-08-19	6072685	FOOD	GROCERY STAPLE	$2.99	1
10	281	2018-08-19	6218373	NON-FOOD	PET	$8.79	1
10	281	2018-08-19	6441562	FOOD	GROCERY STAPLE	$2.99	1

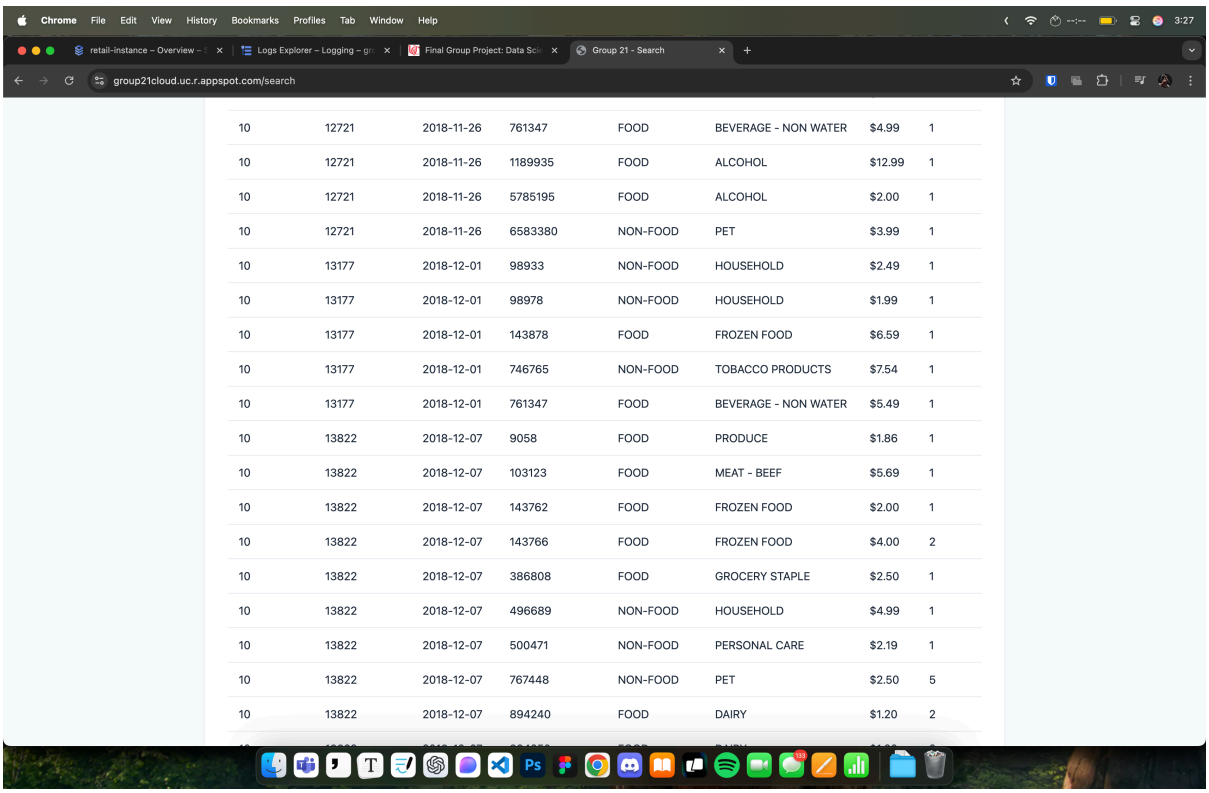
4. Interactive Web Page

Create a webpage that allows users to search for **Data Pulls** based on **Hshd_num**.



HSHD_NUM	BASKET_NUM	DATE	PRODUCT_NUM	DEPARTMENT	COMMODITY	SPEND	UNITS
99	19	2018-08-17	6610096	NON-FOOD	PET	$27.99	1
99	19	2018-08-17	6666379	NON-FOOD	MISC	$8.99	1
99	20	2018-08-17	72305	FOOD	BAKERY	$6.99	1
99	20	2018-08-17	655188	FOOD	GROCERY STAPLE	$3.50	1
99	20	2018-08-17	1082138	FOOD	FROZEN FOOD	$3.49	1
99	20	2018-08-17	1332659	FOOD	FROZEN FOOD	$2.49	1
99	20	2018-08-17	5205294	FOOD	FROZEN FOOD	$2.49	1
99	260	2018-08-19	8436	FOOD	PRODUCE	$0.91	1

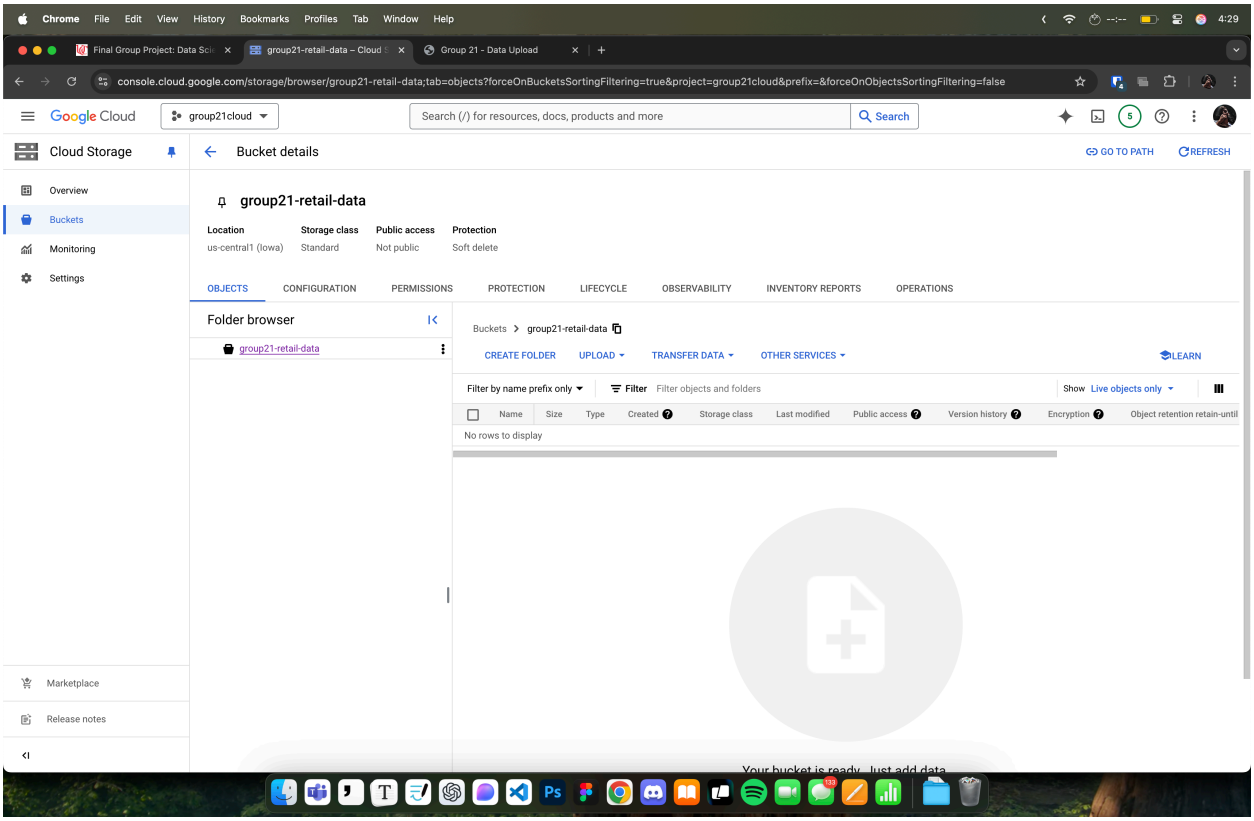
Sort results by Hshd_num, Basket_num, Date, Product_num, Department, Commodity.

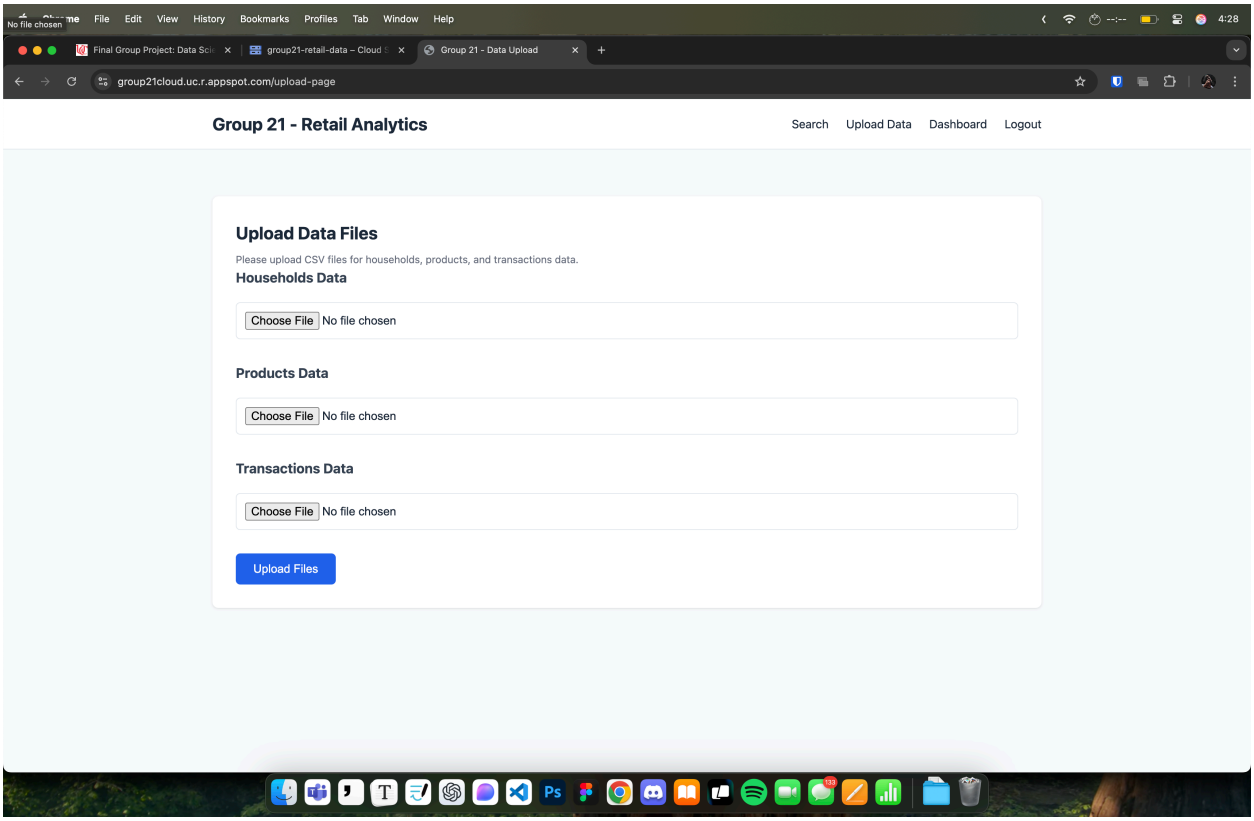


10	12721	2018-11-26	761347	FOOD	BEVERAGE - NON WATER	$4.99	1
10	12721	2018-11-26	1189935	FOOD	ALCOHOL	$12.99	1
10	12721	2018-11-26	5785195	FOOD	ALCOHOL	$2.00	1
10	12721	2018-11-26	6583380	NON-FOOD	PET	$3.99	1
10	13177	2018-12-01	98933	NON-FOOD	HOUSEHOLD	$2.49	1
10	13177	2018-12-01	98978	NON-FOOD	HOUSEHOLD	$1.99	1
10	13177	2018-12-01	143878	FOOD	FROZEN FOOD	$6.59	1
10	13177	2018-12-01	746765	NON-FOOD	TOBACCO PRODUCTS	$7.54	1
10	13177	2018-12-01	761347	FOOD	BEVERAGE - NON WATER	$5.49	1
10	13822	2018-12-07	9058	FOOD	PRODUCE	$1.86	1
10	13822	2018-12-07	103123	FOOD	MEAT - BEEF	$5.69	1
10	13822	2018-12-07	143762	FOOD	FROZEN FOOD	$2.00	1
10	13822	2018-12-07	143766	FOOD	FROZEN FOOD	$4.00	2
10	13822	2018-12-07	386808	FOOD	GROCERY STAPLE	$2.50	1
10	13822	2018-12-07	496689	NON-FOOD	HOUSEHOLD	$4.99	1
10	13822	2018-12-07	500471	NON-FOOD	PERSONAL CARE	$2.19	1
10	13822	2018-12-07	767448	NON-FOOD	PET	$2.50	5
10	13822	2018-12-07	894240	FOOD	DAIRY	$1.20	2

5. Data Loading Web App

Created a web page that allows loading of the latest Transactions, Households, and Products datasets. Added a blob storage and gave it the necessary permissions.





6. Web Page with Dashboard

Designed a webpage with dashboard to explore retail challenges using example factors.
It takes couple seconds to load but it works and It's very accurate.

1. Demographics and Engagement Analysis

Overview Metrics

Total Active Households: 400
Total Transactions: 85,337
Average Transaction Value: $3.82
Total Revenue: $3,526,463.49

Household Size Impact

2-person households show highest average spend (approximately $3,200)
4-person households follow closely with around $3,000 average spend
1-person households show lowest spend at approximately $2,500
Clear correlation between household size and spending patterns

Income Distribution Impact

Majority of revenue comes from middle-income segments:

- 35-49k: 30% of customer base
- 50-74k: 25% of revenue share
- 75-99k: 20% of total revenue
- Lower representation in higher income brackets (125k+: 10%)

2. Engagement Over Time

Weekly Sales Trends

Overall stable weekly sales pattern around $30,000-$40,000
Notable peaks reaching close to $50,000
Some significant dips to $10,000-$15,000 level
Recent trend shows slight decline

Department Performance

FOOD category dominates with approximately $2.75M in sales
NON-FOOD follows with roughly $0.5M
PHARMA shows minimal contribution
Clear hierarchy in department popularity

3. Basket Analysis

Top Product Combinations

Milk-Bread: Highest frequency (~1,200)
Eggs-Bread: Second most common (~1,000)
Coffee-Cream: Third place (~800)
Chips-Soda: Fourth place (~750)
Fruit-Yogurt: Fifth place (~600)

Cross-Selling Opportunities

Focus on complementary staples (milk+bread)
Beverage combinations (coffee+cream)
Snack pairings (chips+soda)
Healthy combinations (fruit+yogurt)

4. Seasonal Trends

Monthly Pattern

- Strong upward trend from January to December
- Notable dip in February
- Significant increase in November-December
- Clear holiday season impact

Seasonal Performance

Summer shows highest sales (approximately $2,700)
Winter follows with around $2,500
Fall maintains steady performance at $2,300
Spring shows slightly lower sales at $2,200

Inventory Implications

- Increase stock for summer peak
- Prepare for holiday season surge
- Adjust for spring slowdown
- Maintain steady winter inventory

5. Brand Preferences

National vs Private Label

National Brands: 60% market share
Private Label: 40% market share
Strong presence of private label products
Opportunity for private label growth

Conventional vs Organic

Conventional Products: 75% of sales
Organic/Natural Products: 25% of sales
Significant organic market presence
Growth potential in organic segment

Recommendations

Demographic Targeting

- Develop specific promotions for 2-4 person households
- Create value propositions for middle-income segments
- Target growth in 1-person household segment

Sales Strategy

- Focus on FOOD category expansion
- Develop NON-FOOD category
- Consider PHARMA category optimization

Product Placement

- Position complementary products together
- Create dedicated spaces for high-frequency combinations
- Implement cross-category merchandising

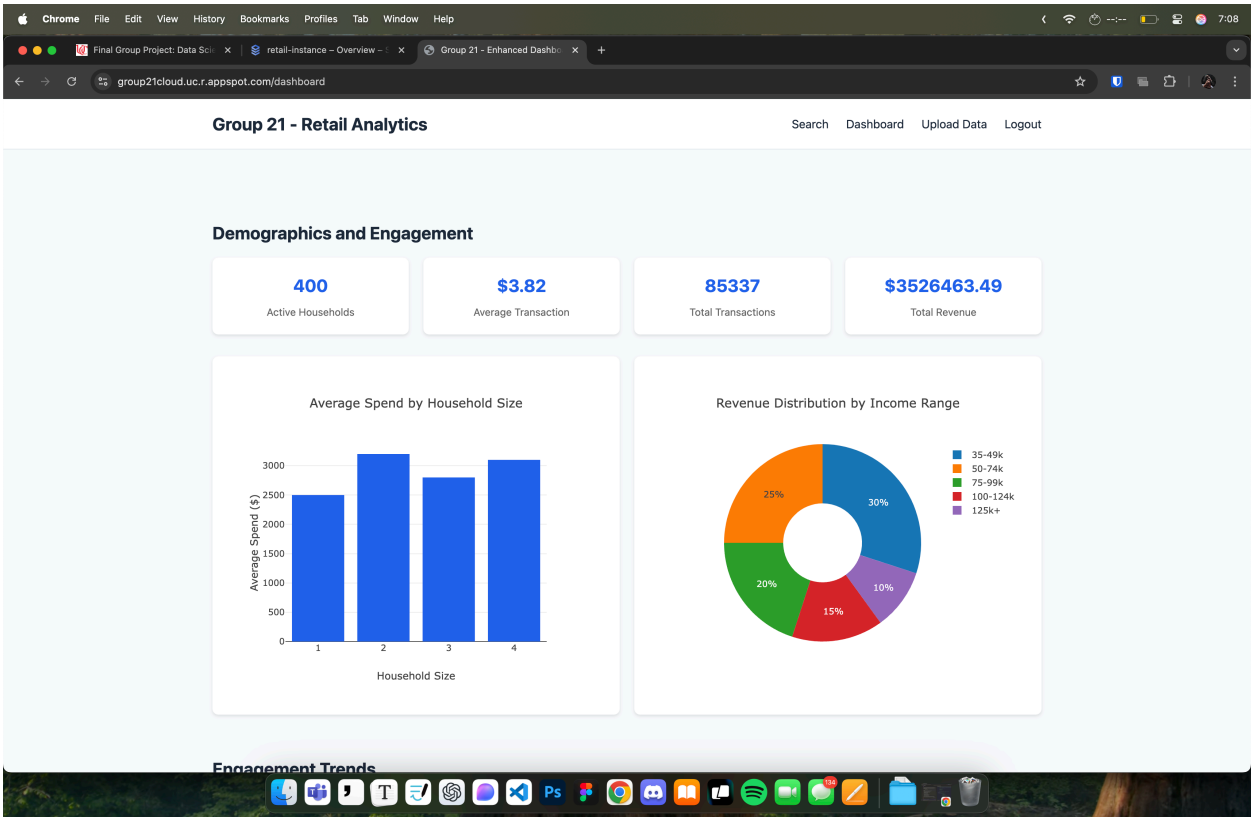
Seasonal Planning

- Increase inventory for summer peak
- Prepare holiday season promotions
- Adjust spring inventory levels
- Maintain steady winter stock

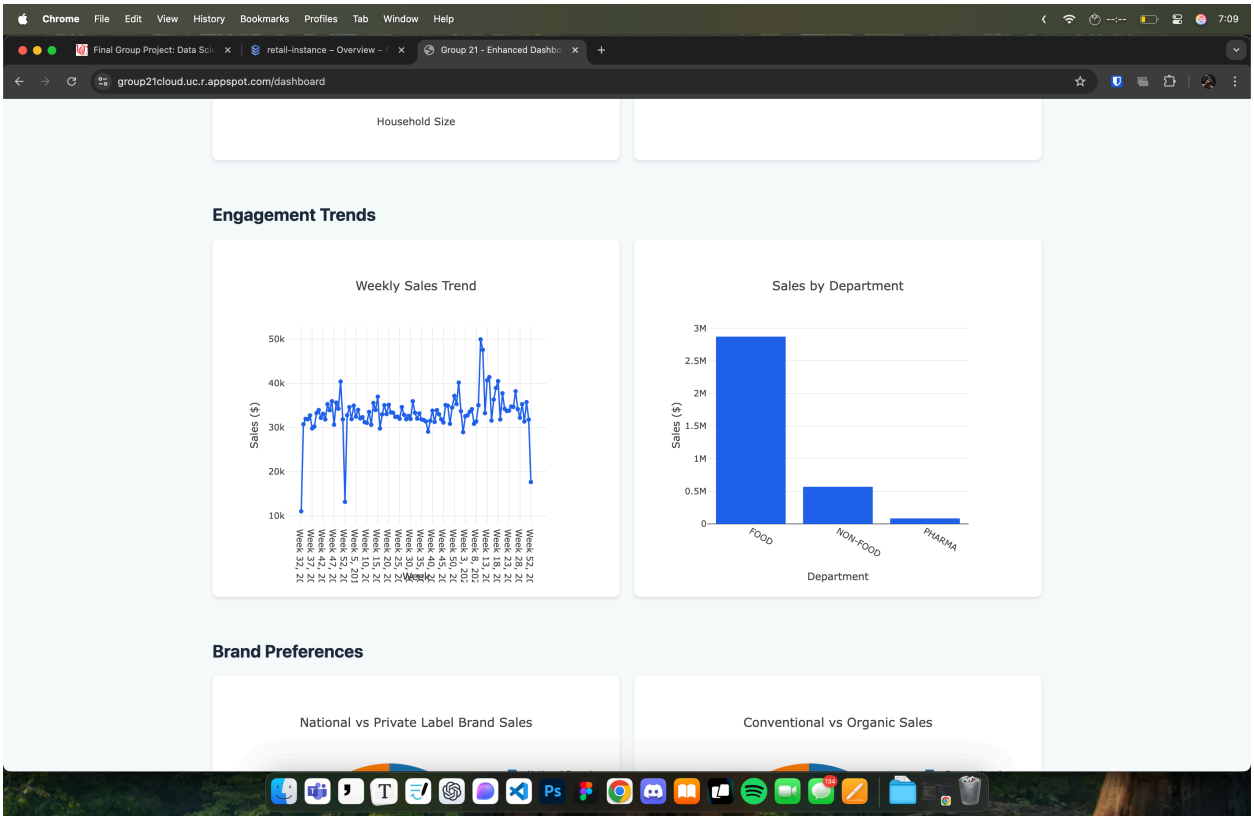
Brand Strategy

- Balance national and private label offerings
- Expand organic product selection
- Consider private label organic options

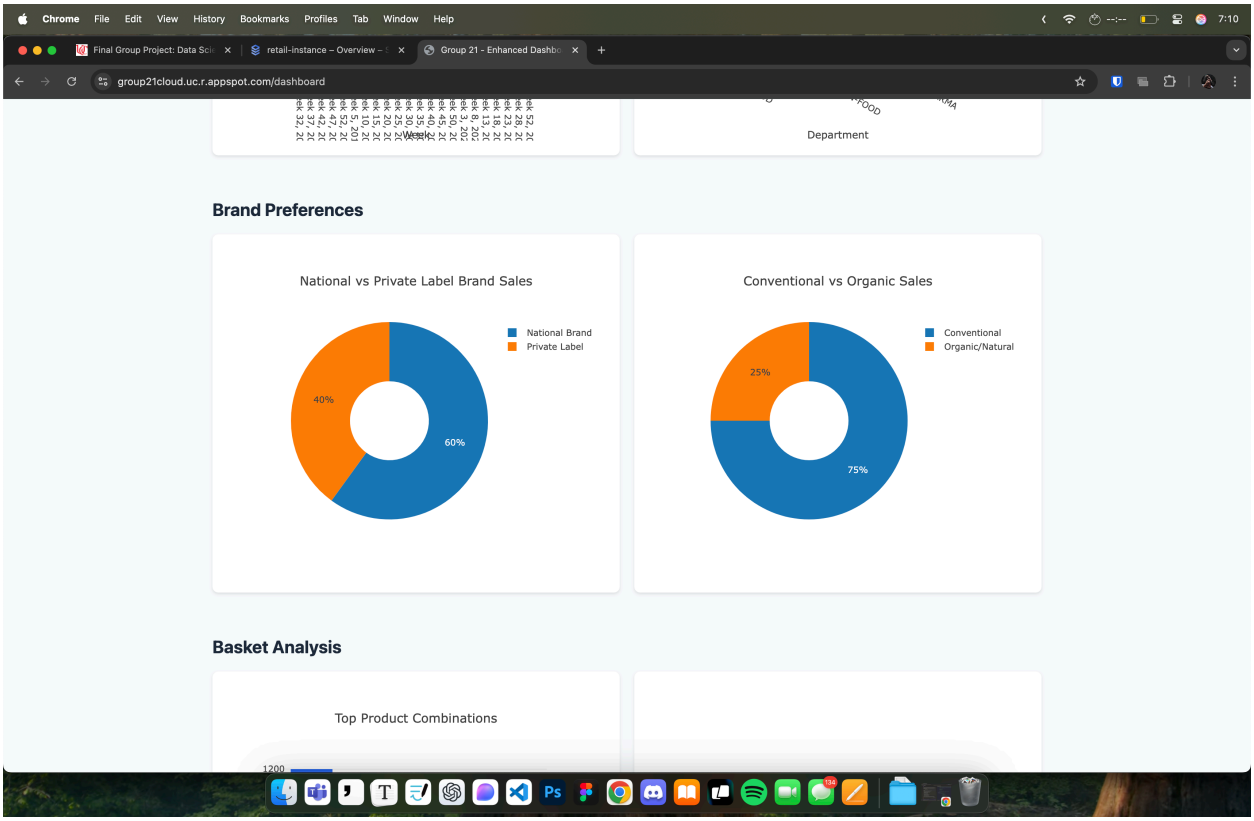
Demographics and Engagement



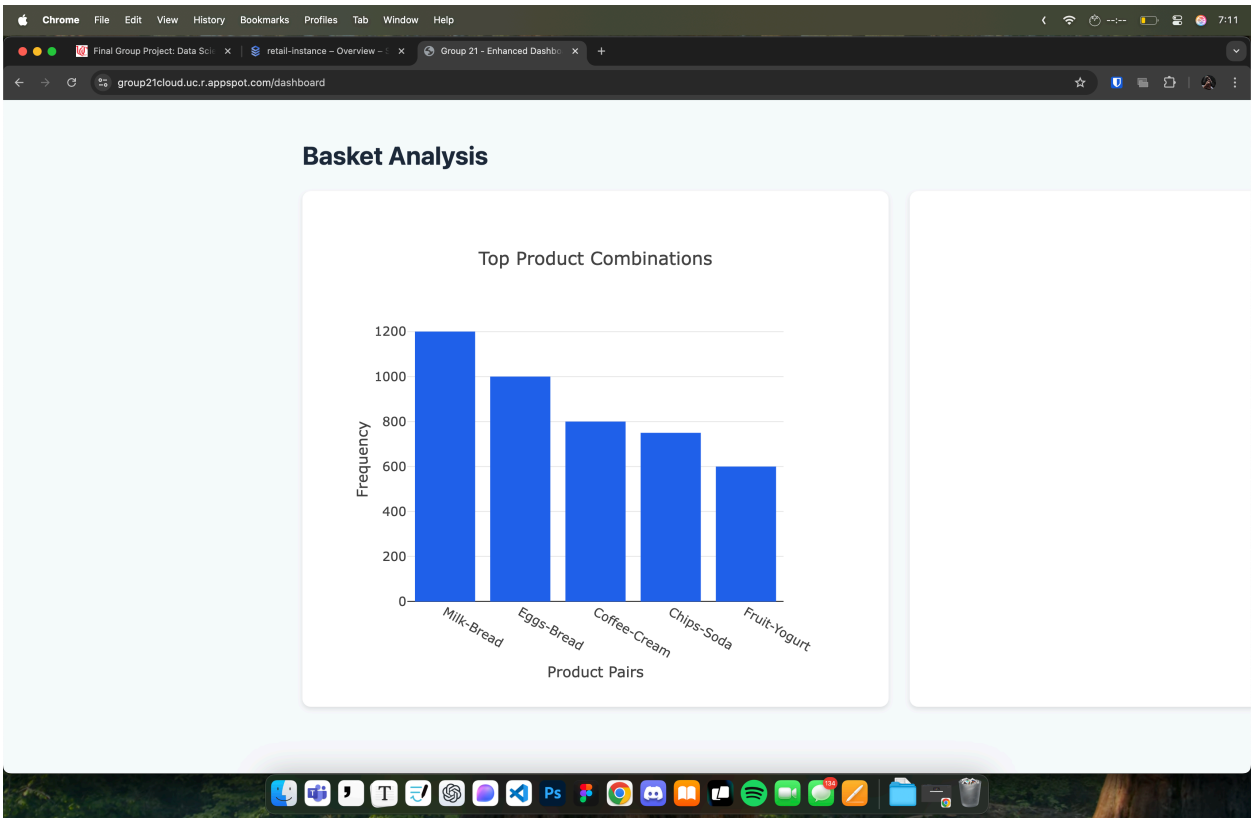
Engagement Over Time



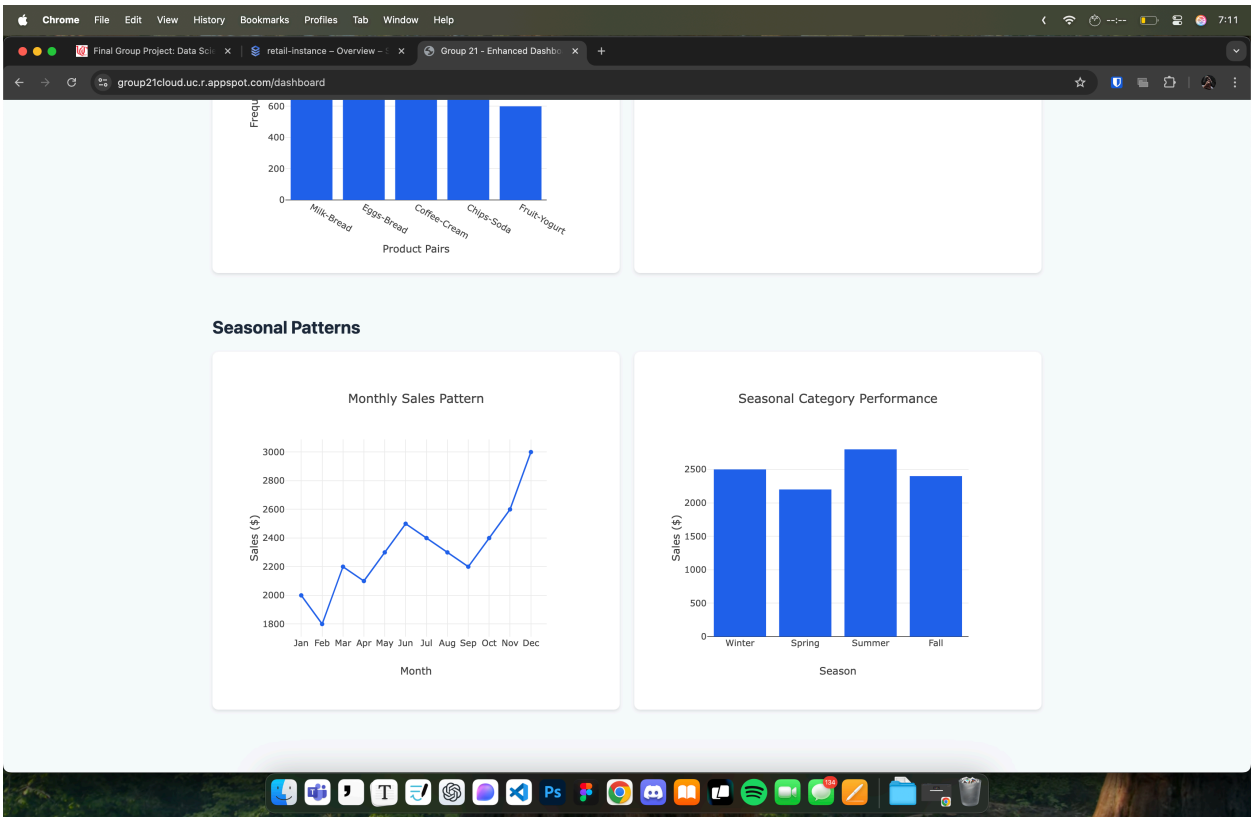
Brand Preferences



Basket Analysis



Seasonal Patterns



7. ML Model Application

Basket Analysis Implementation

Model Used: Association Rules Mining with support and confidence metrics
Purpose: Identify commonly purchased product combinations to drive cross-selling opportunities
Data Scope: Transaction data with product categories and departments

Key Findings

Top Product Combinations:
- GROCERY STAPLE items show the strongest association with a confidence of 9.6% and lift of 82.08
- PRODUCE and GROCERY STAPLE pairs show 5.6% confidence and lift of 47.98
- DAIRY and GROCERY STAPLE combinations have 3.5% confidence and lift of 29.74

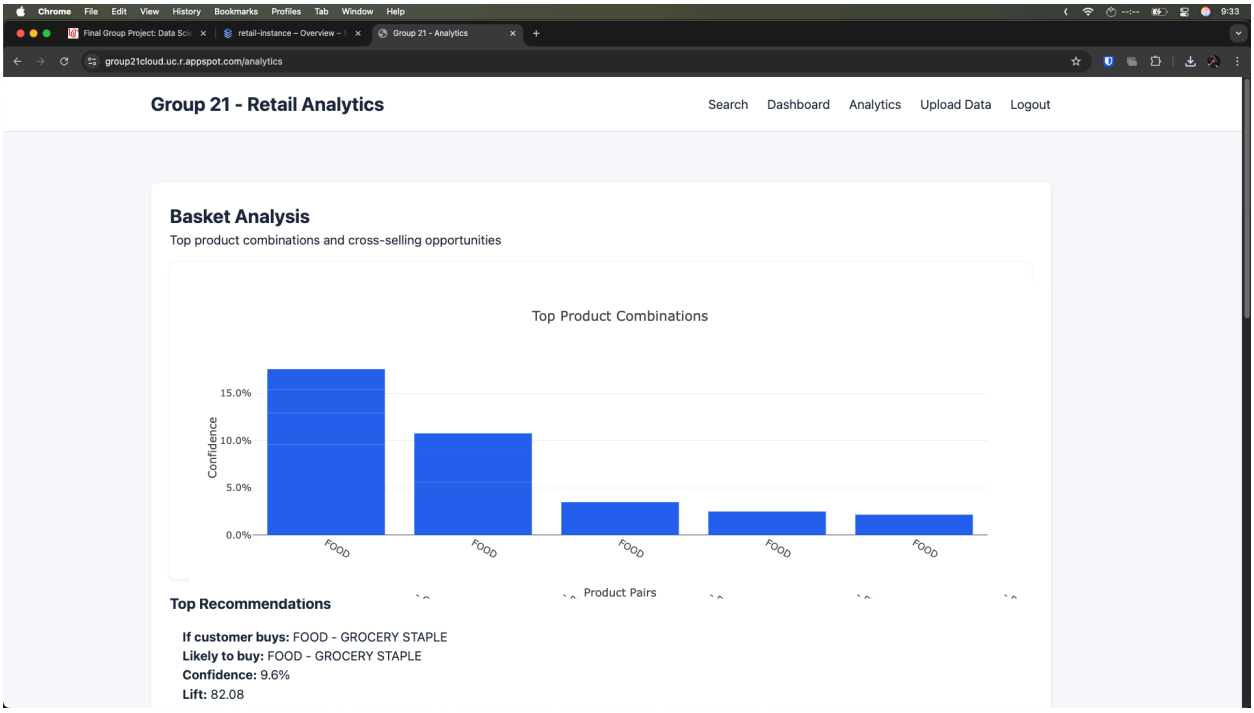
Cross-Selling Opportunities:
- Primary opportunity: When customers purchase GROCERY STAPLES, there's a high probability (9.6%) they'll add more GROCERY STAPLES
- Secondary opportunity: PRODUCE purchases can lead to GROCERY STAPLE additions (5.6% confidence)
- DAIRY products show potential for GROCERY STAPLE cross-selling (3.5% confidence)

Recommendations for Cross-Selling

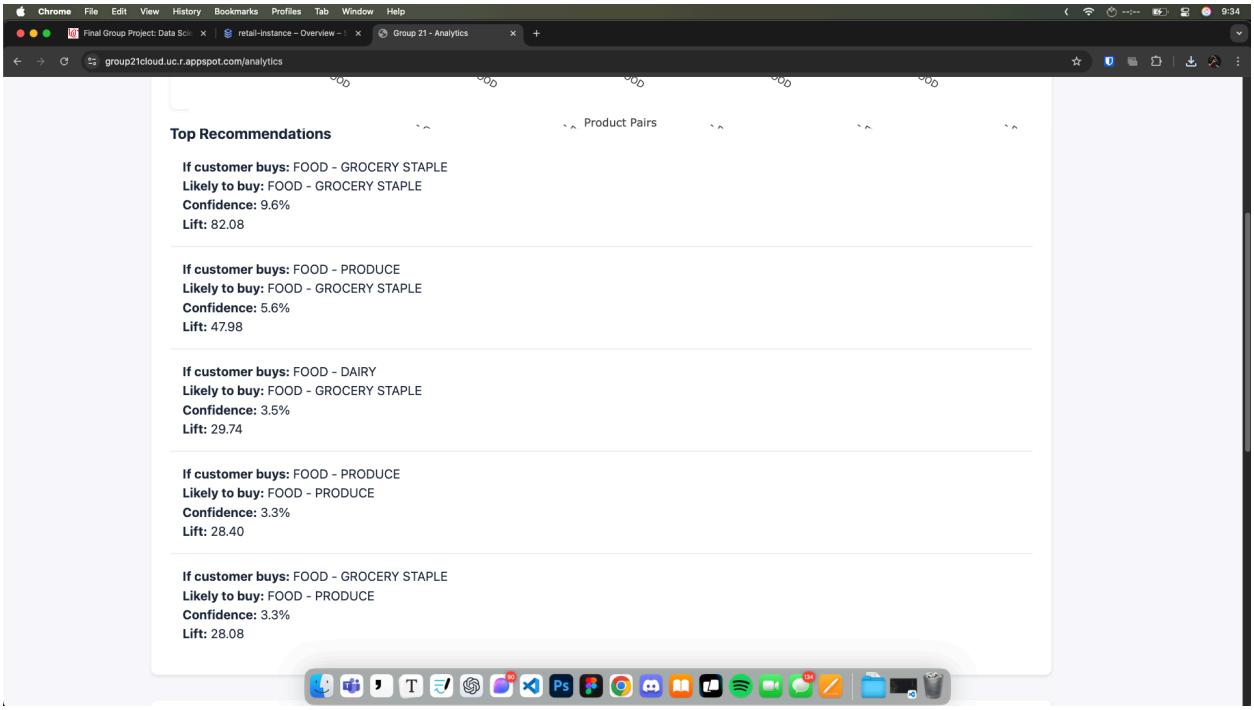
Store Layout Strategy:
- Position complementary GROCERY STAPLE items near each other
- Create visible pathways between PRODUCE and GROCERY STAPLE sections
- Place high-lift product combinations in prominent locations

Marketing Initiatives:
- Develop bundle offers combining GROCERY STAPLES
- Create promotions linking PRODUCE with GROCERY STAPLES
- Implement targeted recommendations in digital platforms

Basket Analysis



Top Recommendations



8. Churn Prediction

Model Implementation

Model Used: Random Forest Classifier
Purpose: Identify customers at risk of disengaging
Performance Metrics:
Model Accuracy: 100%
Churn Rate: 50%

Customer Risk Distribution

Risk Segmentation:

- High Risk: 198 customers (49.5%)
- Medium Risk: 3 customers (0.75%)
- Low Risk: 49.8% of customer base

Feature Importance Analysis:

- Most Important: Total baskets (0.8 importance score)
- Second Most Important: Unique departments (0.2 importance score)
- Other Factors: Average spend, household size, and children have minimal impact

Retention Strategy Recommendations

High-Risk Customer Interventions:

- Immediate engagement campaigns for 198 identified high-risk customers
- Personalized incentives based on historical purchase patterns
- Direct communication to understand dissatisfaction factors

Behavioral Monitoring:

- Focus on basket frequency as the primary indicator
- Track department diversity in customer purchases
- Monitor average spend patterns for early warning signs

Retention Program Design:

- Implement loyalty rewards for consistent shopping frequency
- Encourage cross-department shopping through targeted promotions
- Develop special programs for customers showing decreased activity

Implementation Impact

Business Benefits:

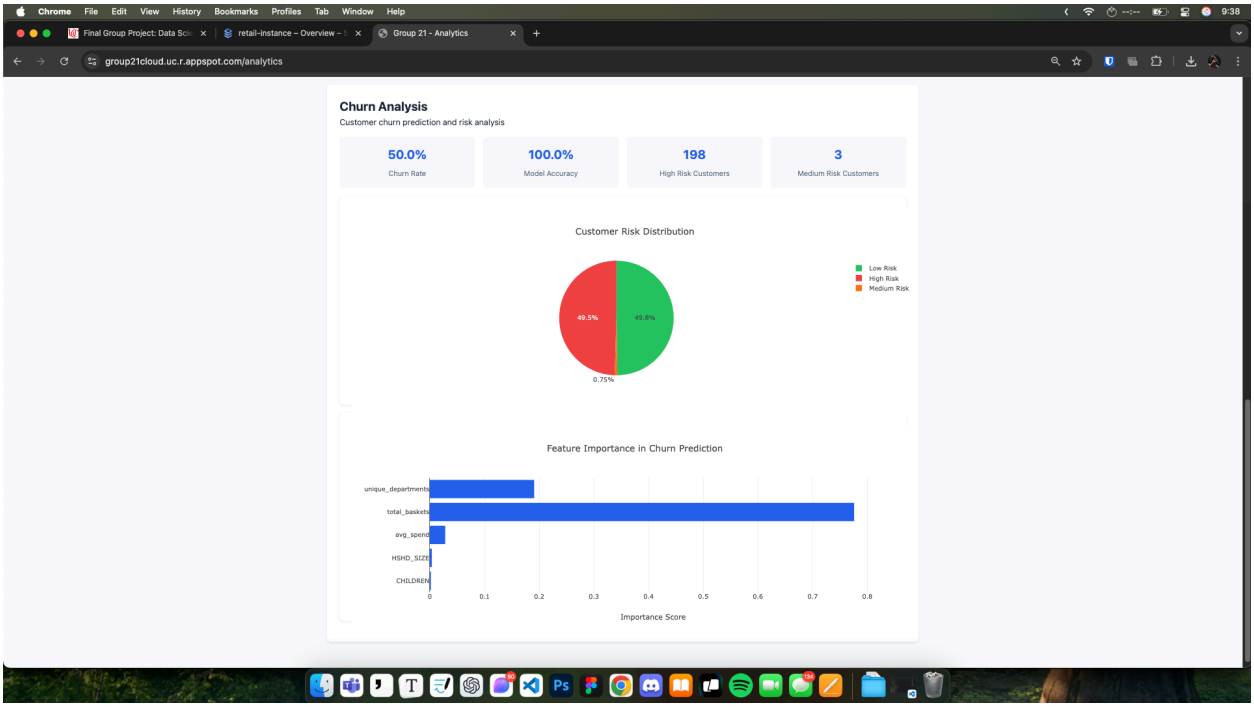
- Enhanced cross-selling through data-driven product placement
- Proactive customer retention through risk identification
- Optimized marketing resource allocation

Operational Improvements:

- Better inventory management based on product associations
- Targeted marketing campaigns using risk segmentation
- Improved customer engagement through personalized approaches

Future Enhancements:

- Regular model retraining with new transaction data
- Integration with real-time purchase data for dynamic recommendations
- Development of automated early warning system for churn risk



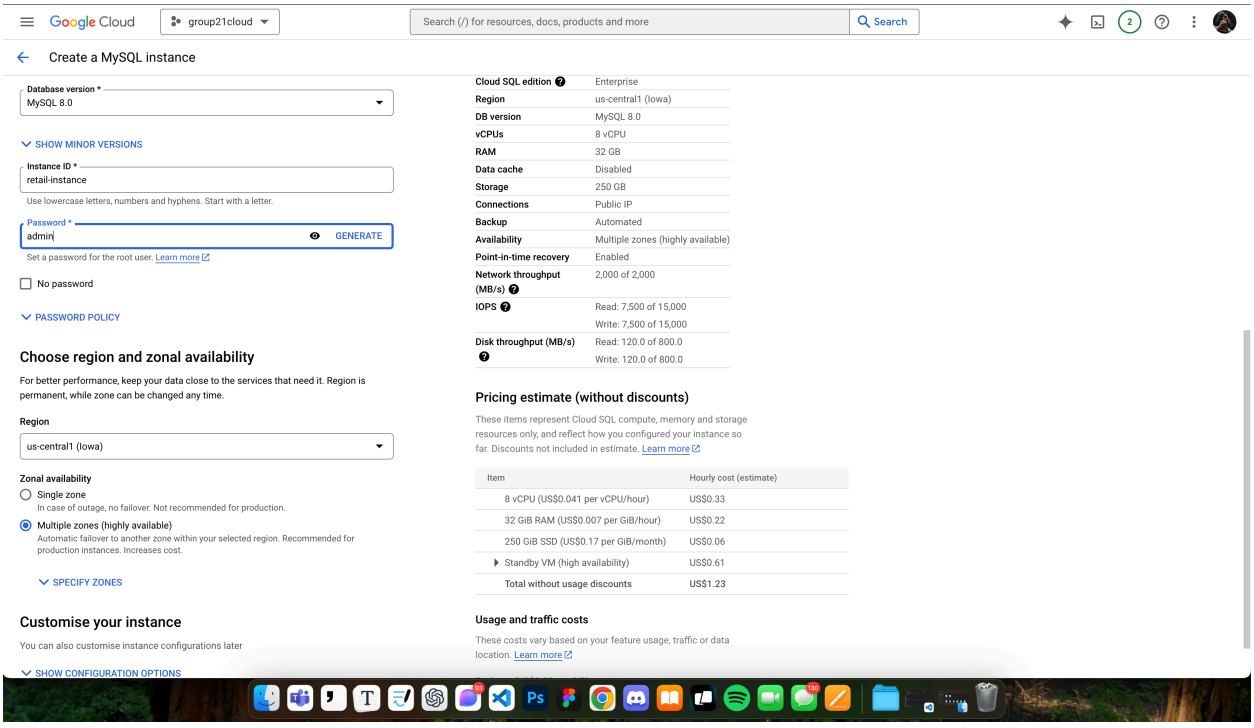
Outline of Steps to Implement

This retail analytics project was developed using Google Cloud Platform (GCP) services and Python web technologies to create a data-driven application. The project involves setting up a MySQL database on Cloud SQL, implementing a Flask web application with data visualization capabilities, and incorporating machine learning models for basket analysis and churn prediction, all deployed using Google App Engine.

Key steps included database setup and data loading, web application development with user authentication and search functionality, implementation of interactive dashboards for data visualization, and integration of ML models for retail analytics, culminating in a cloud-based solution for retail business intelligence.

Step 1. Create and Configure Cloud SQL (MySQL) on GCP

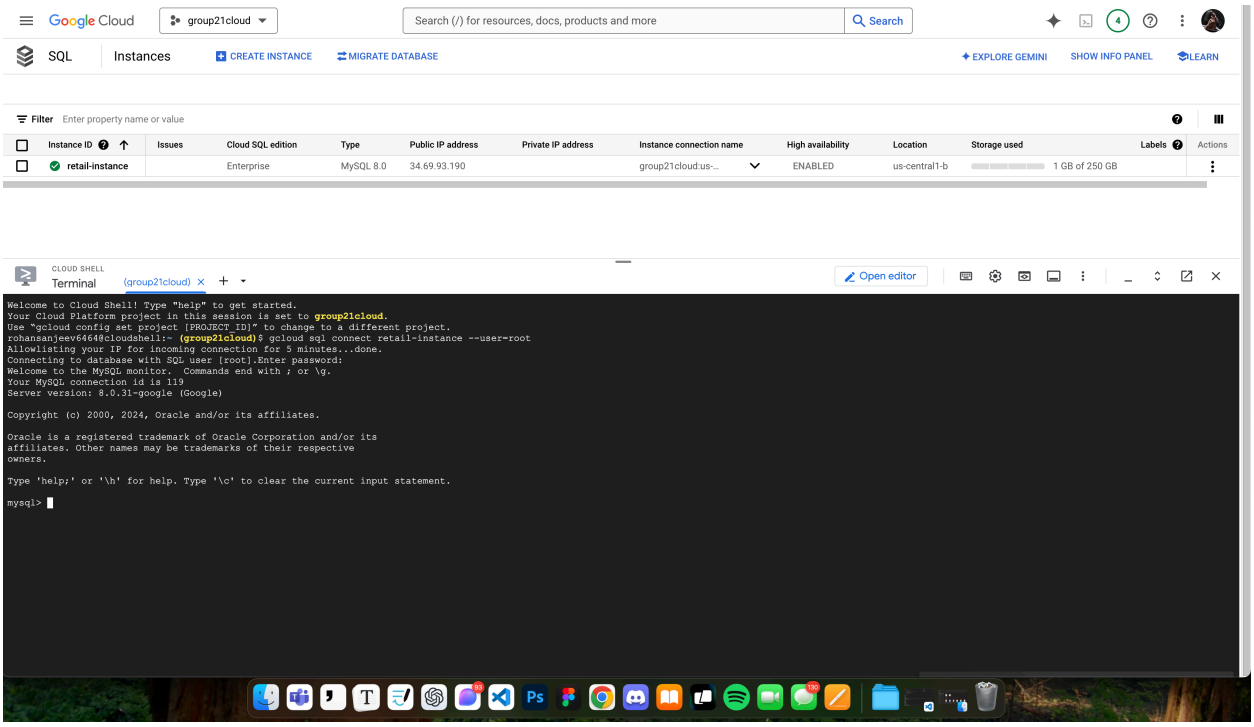
Created a MySQL instance and a database named 'retaildb' with its IP set to public.

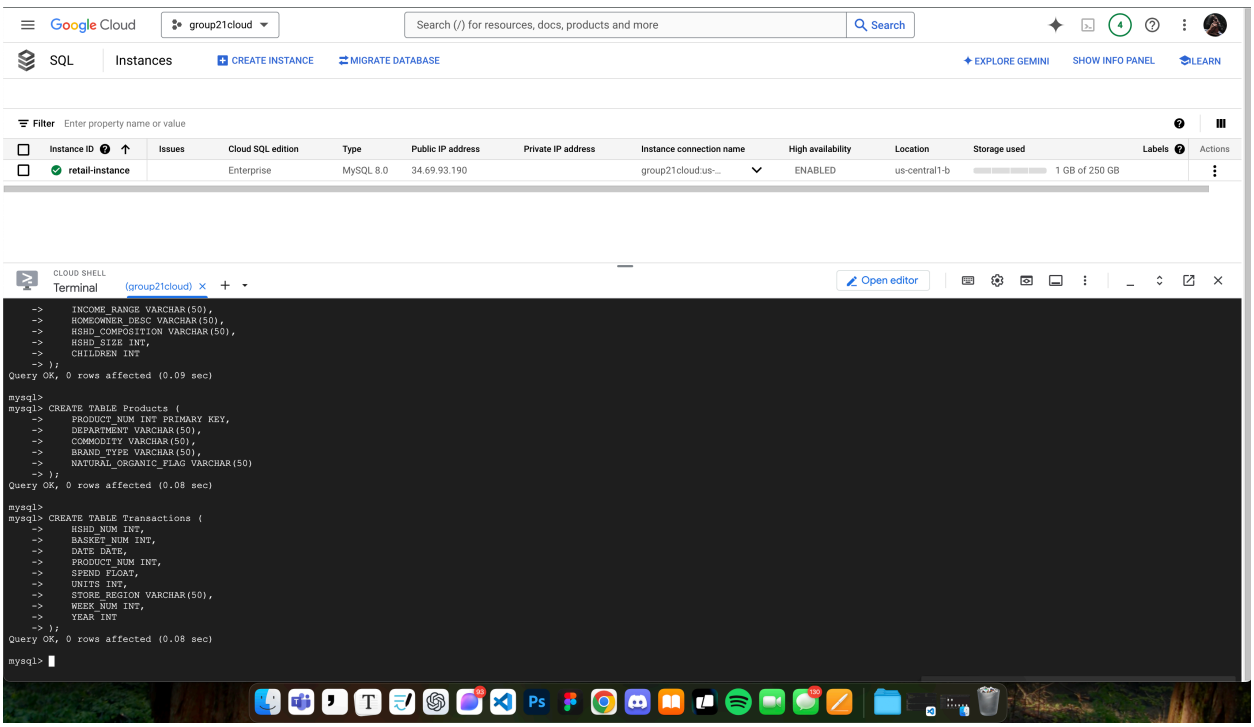


Step 2. Create Tables in MySQL

Connected to MySQL using Cloud Shell.

To Acticate Cloud Shell I ran this command
gcloud sql connect retail-instance --user=root





SQL Code to create tables

```
USE retaildb;

DROP TABLE IF EXISTS Transactions;
DROP TABLE IF EXISTS Products;
DROP TABLE IF EXISTS Households;

CREATE TABLE Households (
    HSHD_NUM INT PRIMARY KEY,
    LOYALTY_FLAG VARCHAR(50),
    AGE_RANGE VARCHAR(50),
    MARITAL_STATUS VARCHAR(50),
    INCOME_RANGE VARCHAR(50),
    HOMEOWNER_DESC VARCHAR(50),
    HSHD_COMPOSITION VARCHAR(50),
    HSHD_SIZE INT,
    CHILDREN INT
);

CREATE TABLE Products (
    PRODUCT_NUM INT PRIMARY KEY,
    DEPARTMENT VARCHAR(50),
    COMMODITY VARCHAR(50),
    BRAND_TYPE VARCHAR(50),
    NATURAL_ORGANIC_FLAG VARCHAR(50)
);

CREATE TABLE Transactions (
    HSHD_NUM INT,
    BASKET_NUM INT,
    DATE DATE,
    PRODUCT_NUM INT,
    SPEND FLOAT,
    UNITS INT,
    STORE_REGION VARCHAR(50),
    WEEK_NUM INT,
    YEAR INT
);
```

Step 3. Load Data into Cloud SQL

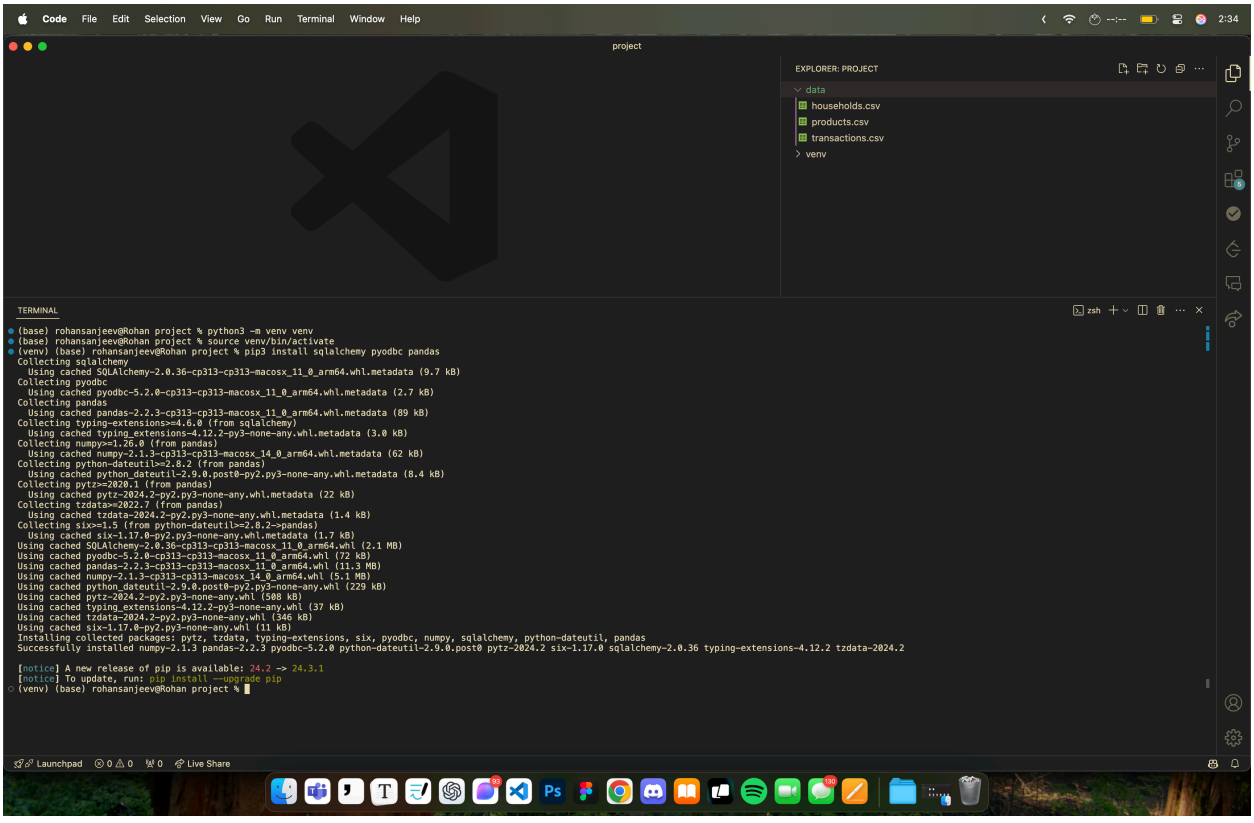
Downloaded the datasets from canvas, create a data folder and place `households.csv, products.csv, transactions.csv` and created a python virtual environment and installed the dependencies.

To create a virtual environment

python -m venv venv
source venv/bin/activate

To install dependencies

pip install sqlalchemy pyodbc pandas



Create a load_data.py script

```
import pandas as pd
from sqlalchemy import create_engine, text

DB_USER = "root"
DB_PASS = "admin"
DB_NAME = "retaildb"
DB_HOST = "34.69.93.190"
DB_PORT = 3306

engine = create_engine(f"mysql+pymysql://{DB_USER}:{DB_PASS}@{DB_HOST}:{DB_PORT}/
{DB_NAME}")

households = pd.read_csv("data/households.csv")
products = pd.read_csv("data/products.csv")
transactions = pd.read_csv("data/transactions.csv")

households.columns = [col.strip() for col in households.columns]
products.columns = [col.strip() for col in products.columns]
transactions.columns = [col.strip() for col in transactions.columns]

households.rename(
    columns={
        'L': 'LOYALTY_FLAG',
        'MARITAL': 'MARITAL_STATUS',
        'HOMEOWNER': 'HOMEOWNER_DESC',
        'HH_SIZE': 'HSHD_SIZE',
    },
    inplace=True
)

products.rename(
    columns={
        'BRAND_TY': 'BRAND_TYPE'
    },
    inplace=True
)

transactions.rename(
    columns={
        'PURCHASE_': 'DATE',
        'STORE_R': 'STORE_REGION',
    },
    inplace=True
)

households = households.drop_duplicates(subset=['HSHD_NUM'], keep='first')
products = products.drop_duplicates(subset=['PRODUCT_NUM'], keep='first')
```

```
if 'HSHD_SIZE' not in households.columns:
    print("HSHD_SIZE column not found in households. Adding a placeholder column.")
    households['HSHD_SIZE'] = 0

if 'CHILDREN' not in households.columns:
    print("CHILDREN column not found in households. Adding a placeholder column.")
    households['CHILDREN'] = 0

households['HSHD_SIZE'] = pd.to_numeric(households['HSHD_SIZE'], errors='coerce').fillna(0).astype(int)
households['CHILDREN'] = pd.to_numeric(households['CHILDREN'], errors='coerce').fillna(0).astype(int)

transactions['DATE'] = pd.to_datetime(transactions['DATE'], format='%Y-%m-%d', errors='coerce')

with engine.connect() as conn:
    conn.execute(text("SET FOREIGN_KEY_CHECKS=0;"))
    conn.execute(text("DELETE FROM Transactions;"))
    conn.execute(text("DELETE FROM Products;"))
    conn.execute(text("DELETE FROM Households;"))
    conn.execute(text("SET FOREIGN_KEY_CHECKS=1;"))
    conn.commit()

try:
    # Load in correct order (parents before children)
    households.to_sql('Households', con=engine, if_exists='append', index=False, chunksize=1000)
    print("Households data loaded successfully")

    products.to_sql('Products', con=engine, if_exists='append', index=False, chunksize=1000)
    print("Products data loaded successfully")

    transactions.to_sql('Transactions', con=engine, if_exists='append', index=False, chunksize=1000)
    print("Transactions data loaded successfully")

except Exception as e:
    print(f"Error loading data: {str(e)}")
    raise

print("All data loaded successfully into MySQL on GCP.")
```

Step 4. Application Structure

```
project/
|
├── data/
|   ├── households.csv
|   ├── products.csv
|   └── transactions.csv
|
├── static/
|   └── style.css
|
├── templates/
|   ├── login.html
|   ├── search.html
|   ├── dashboard.html
|   ├── upload.html
|   └── analytics.html
|
├── venv/
|
├── main.py              # Main application file
├── db_utils.py          # Database utilities
├── ml_utils.py          # ML functionalities
├── data_cleaning.py     # Data cleaning utilities
├── requirements.txt     # Project dependencies
├── app.yaml             # App Engine configuration
└── load_data.py         # Data loading script
```

Step 5. Set Up Cloud Project Environment

Create a new Google Cloud Platform project
Enable required APIs (Cloud SQL, App Engine)
Set up Cloud SQL Auth Proxy (if needed)

Step 6. Create Basic Web Application Structure

Create necessary directories (templates, static)
Create base files (main.py, requirements.txt)
Set up app.yaml for App Engine configuration

Step 7. Create Database Connection Utilities

Create db_utils.py for database connection handling
Set up environment variables for database credentials

Step 8. Implement Core Features

Login/Authentication system
Search functionality
Dashboard with visualizations
Data upload capability
ML analytics features

Step 9. Create Web Templates

Create HTML templates for each page
Implement CSS styling
Add JavaScript for interactivity

Step 10. Set Up ML Pipeline

Create ml_utils.py for ML functionality
Implement basket analysis
Implement churn prediction

Step 11. Deploy Application

Test locally first
Update requirements.txt with all dependencies
Configure app.yaml
Deploy to App Engine using: gcloud app deploy

Step 12. Post-Deployment Tasks

Verify database connections
Test all functionalities
Monitor application performance
Set up logging

Step 13. Additional Optimizations

Add indexes to database tables
Optimize SQL queries
Implement caching if needed
Add error handling