ETL Project - First Delivery: Credit Card Transactions

Repository

Looker Dashboard

Notion Page

Kaggle Dataset

Team dev

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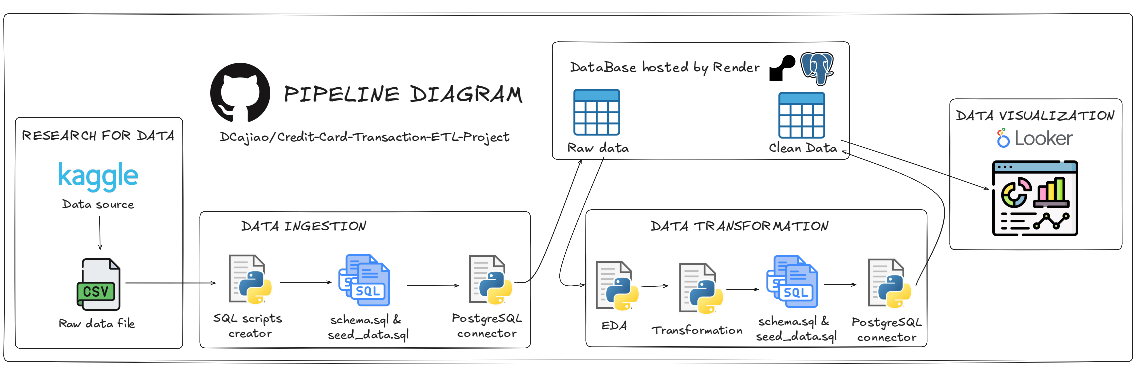
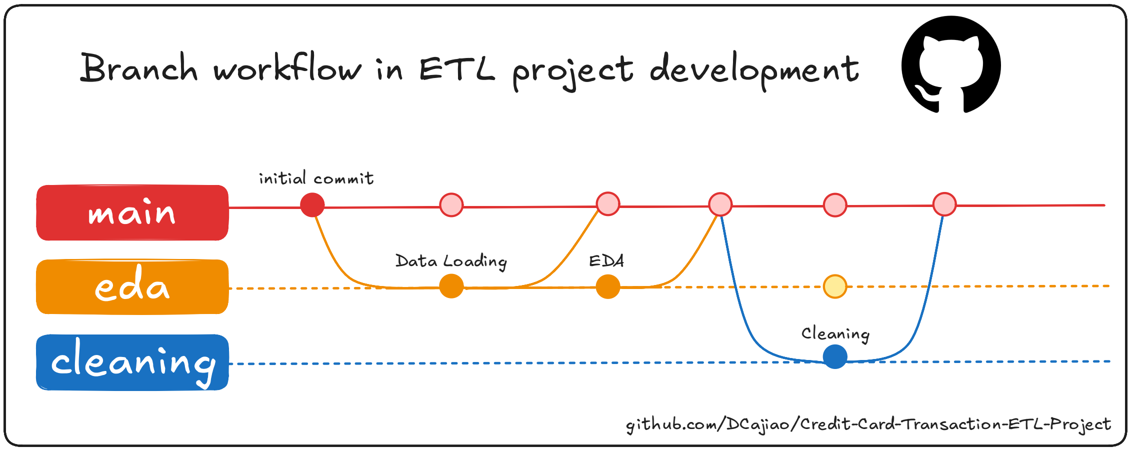
Introduction

This report provides a detailed overview of the ETL (Extract, Transform, Load) process performed in this project, focusing on the specific tasks performed at each step, the key results and the relevance of certain tools and scripts, such as `pysqlschema.py`. The goal was to build a robust pipeline for analyzing credit card transaction data, from data ingestion to final visualization.

The following diagram was designed for the pipeline to be created in the development of the project



In addition, being a team project, the following work plan was developed by branches



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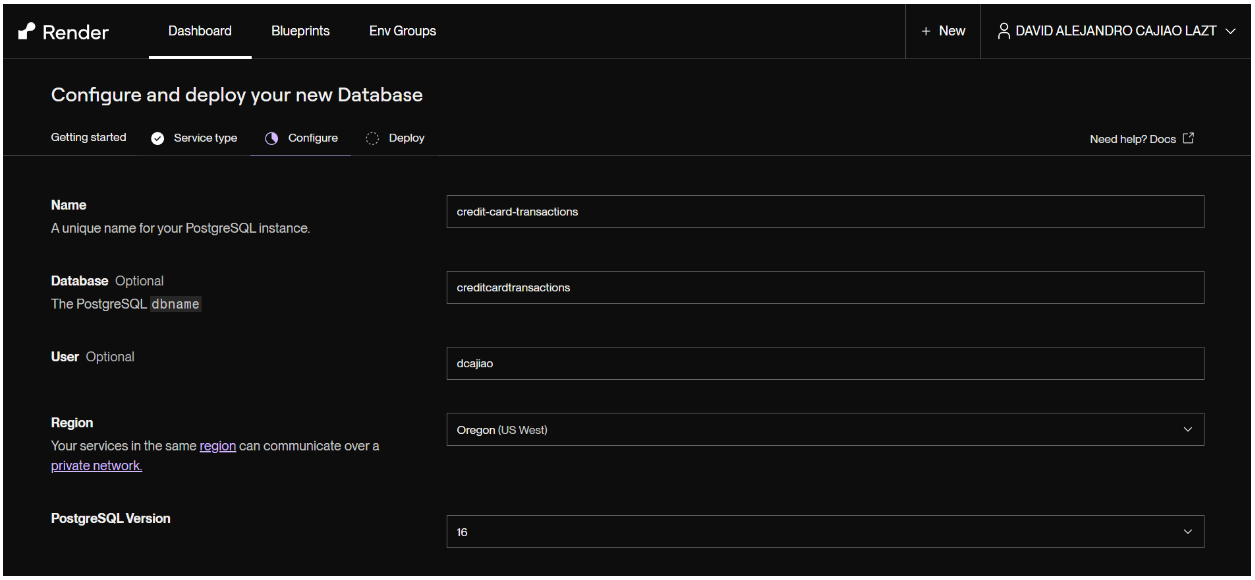
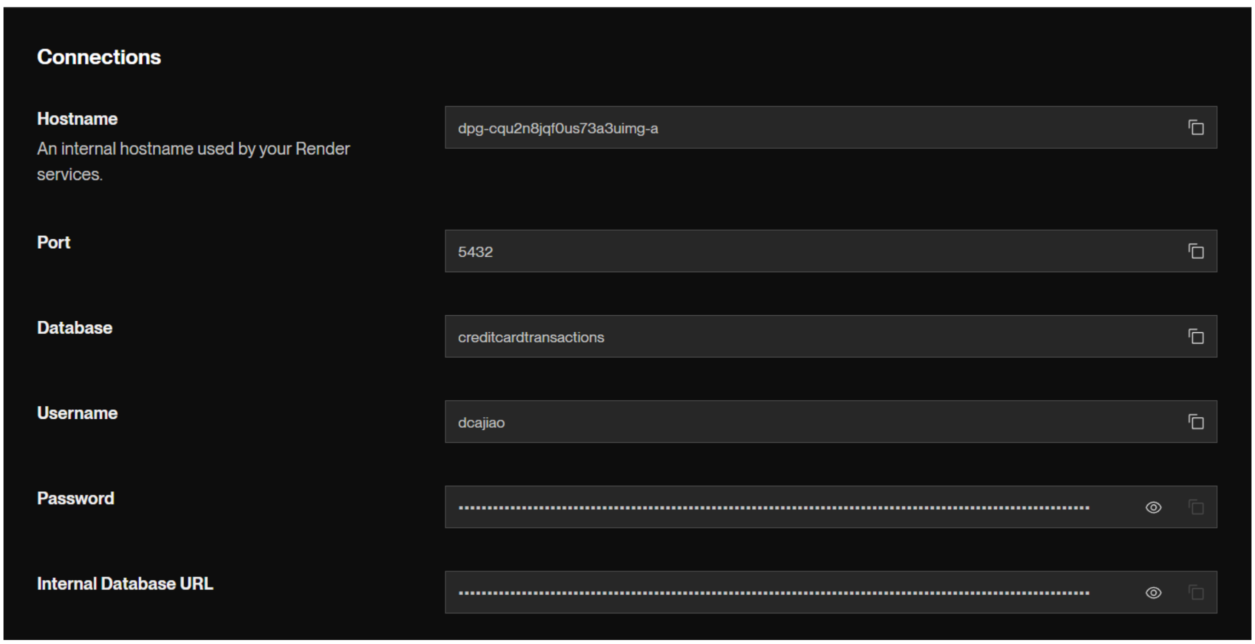
1. Data Loading (`00_data_load.ipynb`)

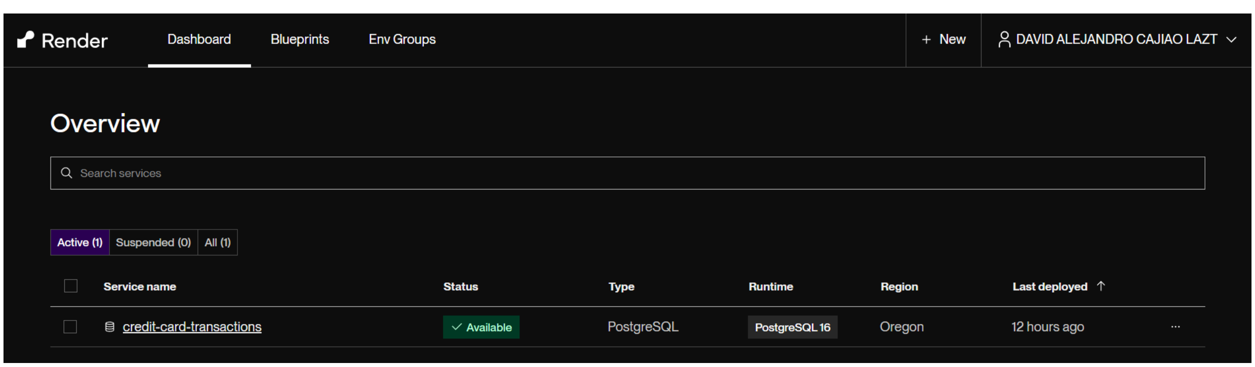
What was done?

The first step in the ETL pipeline involved loading the raw candidate data into a PostgreSQL database. The raw data was provided in CSV format and needed to be uploaded to a relational database to facilitate structured queries and further analysis.

- **Database Setup:** A connection was established to a free PostgreSQL instance deployed on **Render**. This cloud instance enabled efficient and scalable remote access.
- **Implementation Documentation:** Detailed public documentation was written by DCajiao to guide other users in creating and deploying databases on Render. This document is an essential resource for those looking to replicate the development environment.
- **Data Ingestion:** The raw data was read using Pandas and inserted into the corresponding tables in the database. The schema for these tables was previously defined in the `schema.sql` file, which was applied before the data load using `seed_data.sql`. For this it was necessary to perform a batch upload due to the size of the df


Render
Dashboard
Blueprints
Env Groups
+ New
DAVID ALEJANDRO CAJIAO LAZT
Configure and deploy your new Database
Getting started
Service type
Configure
Deploy
Need help? Docs
Name
A unique name for your PostgreSQL instance.
credit-card-transactions
Database Optional
The PostgreSQL dbname
creditcardtransactions
User Optional
dcajiao
Region
Your services in the same region can communicate over a private network.
Oregon (US West)
PostgreSQL Version
16

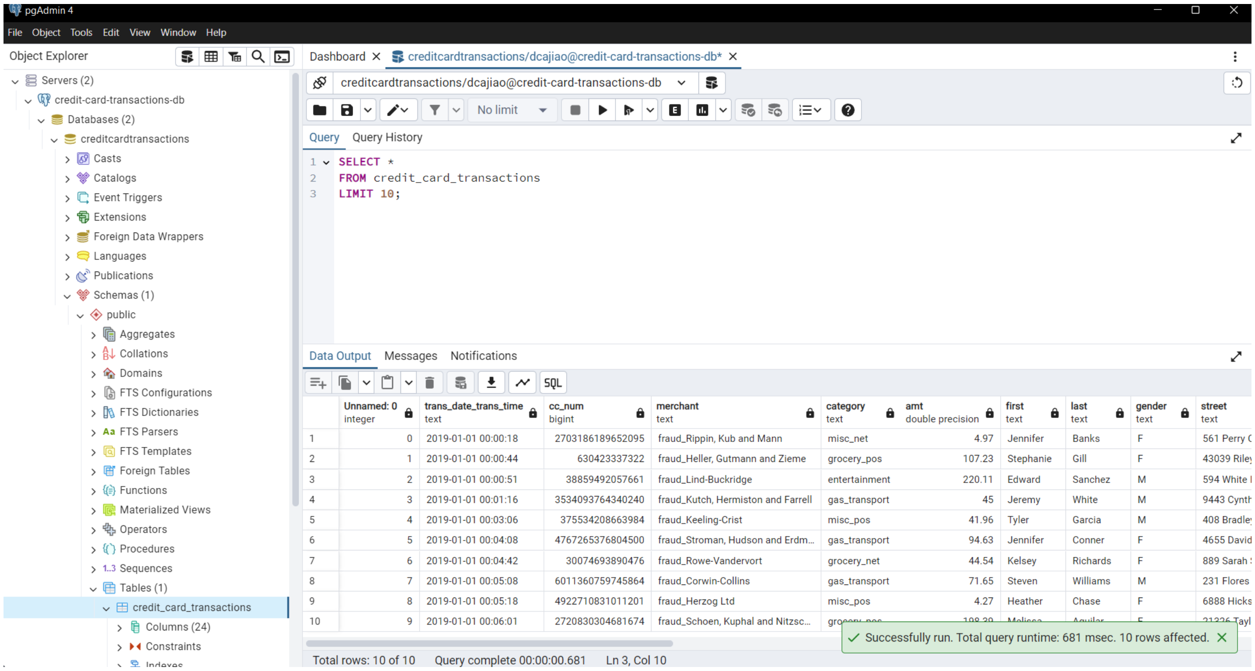

Connections
Hostname
An internal hostname used by your Render services.
dpg-cqu2n8jqf0us73a3uimg-a
Port
5432
Database
creditcardtransactions
Username
dcajiao
Password
Internal Database URL


Render
Dashboard
Blueprints
Env Groups
+ New
DAVID ALEJANDRO CAJIAO LAZT
Overview
Search services
Active (1)
Suspended (0)
All (1)
Service name
Status
Type
Runtime
Region
Last deployed
credit-card-transactions
Available
PostgreSQL
PostgreSQL 16
Oregon
12 hours ago

```python
# Seed data by executing the seed data script in batches
db.execute_in_batches("../sql/seed_data.sql", batch_size=20000)
```

✓ 16m 59.4s

```
2024-08-24 15:47:42,250 - ✓ Connected to database
2024-08-24 15:47:57,498 - ✓ Executed a batch of 20000 records
2024-08-24 15:48:11,525 - ✓ Executed a batch of 20000 records
2024-08-24 15:48:25,106 - ✓ Executed a batch of 20000 records
2024-08-24 15:48:39,384 - ✓ Executed a batch of 20000 records
2024-08-24 15:49:02,796 - ✓ Executed a batch of 20000 records
2024-08-24 15:49:16,940 - ✓ Executed a batch of 20000 records
2024-08-24 15:49:29,923 - ✓ Executed a batch of 20000 records
2024-08-24 15:49:40,716 - ✓ Executed a batch of 20000 records
2024-08-24 15:50:01,950 - ✓ Executed a batch of 20000 records
2024-08-24 15:50:16,156 - ✓ Executed a batch of 20000 records
2024-08-24 15:50:29,853 - ✓ Executed a batch of 20000 records
2024-08-24 15:50:45,723 - ✓ Executed a batch of 20000 records
2024-08-24 15:51:07,141 - ✓ Executed a batch of 20000 records
2024-08-24 15:51:21,095 - ✓ Executed a batch of 20000 records
2024-08-24 15:51:31,892 - ✓ Executed a batch of 20000 records
2024-08-24 15:51:43,005 - ✓ Executed a batch of 20000 records
2024-08-24 15:52:05,710 - ✓ Executed a batch of 20000 records
2024-08-24 15:52:19,108 - ✓ Executed a batch of 20000 records
2024-08-24 15:52:32,298 - ✓ Executed a batch of 20000 records
2024-08-24 15:52:50,531 - ✓ Executed a batch of 20000 records
2024-08-24 15:53:11,501 - ✓ Executed a batch of 20000 records
2024-08-24 15:53:25,222 - ✓ Executed a batch of 20000 records
2024-08-24 15:53:38,885 - ✓ Executed a batch of 20000 records
2024-08-24 15:54:01,605 - ✓ Executed a batch of 20000 records
2024-08-24 15:54:19,219 - ✓ Executed a batch of 20000 records
2024-08-24 15:54:32,855 - ✓ Executed a batch of 20000 records
2024-08-24 15:54:46,171 - ✓ Executed a batch of 20000 records
2024-08-24 15:55:00,209 - ✓ Executed a batch of 20000 records
2024-08-24 15:55:13,775 - ✓ Executed a batch of 20000 records
```



2. Data Exploration (01_EDA.ipynb)

What was done?

The second step involved exploring the data to understand its structure, content, and potential issues. This step was crucial to identifying the necessary transformations to clean and prepare the data for analysis.

- **Initial Query:** SQL queries were executed directly on the database to obtain the dataframe and process it further from the local environment.
- **Exploratory Data Analysis (EDA):** An EDA was performed using Pandas to generate descriptive statistics, identify outliers, and visualize distributions. This helped to understand the overall shape and characteristics of the dataset.

Key Findings

Results:

1. The dataset has 1.2M records and 24 columns.
2. We have 1 candidate column to be the ID (`Unnamed: 0`).
3. We have 4 relevant categorical columns (`category` , `gender` , `state` , `job` , `is_fraud`).
4. We have 2 relevant numerical columns (`cc_num` , `amt`).
5. We have 2 relevant date columns (`trans_date_trans_time` , `dob`)

3. Data Cleaning (02_cleaning.ipynb)

What was done?

Data cleaning was an essential step to ensure the quality and usability of the dataset for analysis. The process involved the following steps:

- Column `Unnamed: 0` should be renamed to `id`.

  From the EDA we identified that this column was the best candidate to become the records ID.

- The `trans_date_trans_time` column should be loaded as `datetime`.
- The `dob` column should be loaded as `datetime`.
- Column `cc_num` should be loaded as string.

  From the EDA we identified that this column was the best candidate to become the customer ID.

- Remove the `unix_time`, `city_pop`, `merch_lat`, `merch_long`, columns.

  We used only certain columns to perform the analysis and these were discarded.

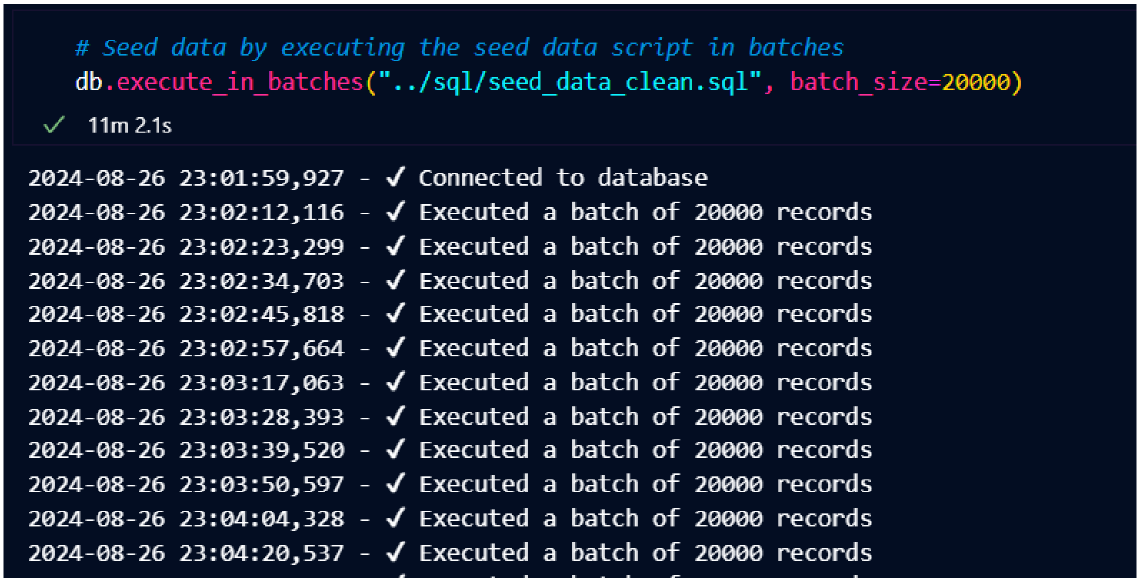
- Remove records with null values.

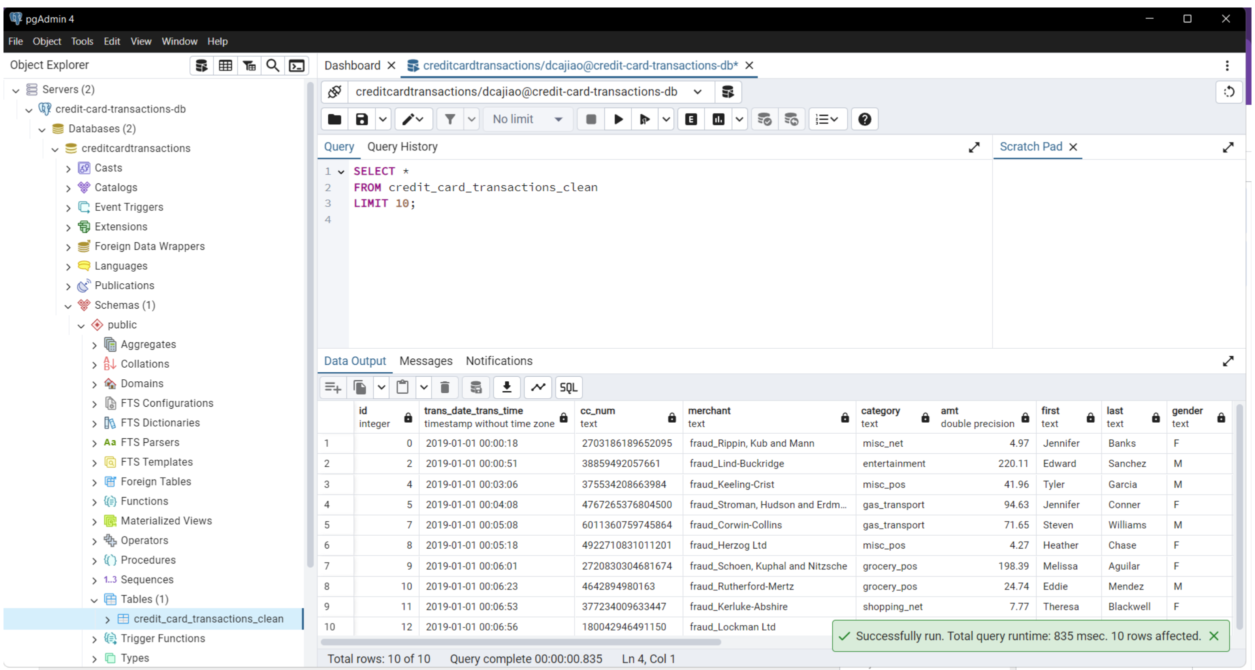
  From the EDA we knew that the zipmerchan column was the one with nulls, and that was because they were virtual merchants, so we decided to focus our analysis on physical merchants.

- Convert `is_fraud` to boolean.
- Calculate the `age` of the customers and convert it to a new column.
- Remove records whose `age` is less than 21 years old.

  This is because, at least in the USA, people can use credit cards from the age of 21.

Afterward, we proceeded with the Database Update: After cleaning, the data was updated in the database in the `candidates_cleaned` table, ensuring that the database reflected the cleanest and most prepared version of the data. In addition, it was necessary to immediately delete the previous table because the free render instance we are using did not allow us that much space.



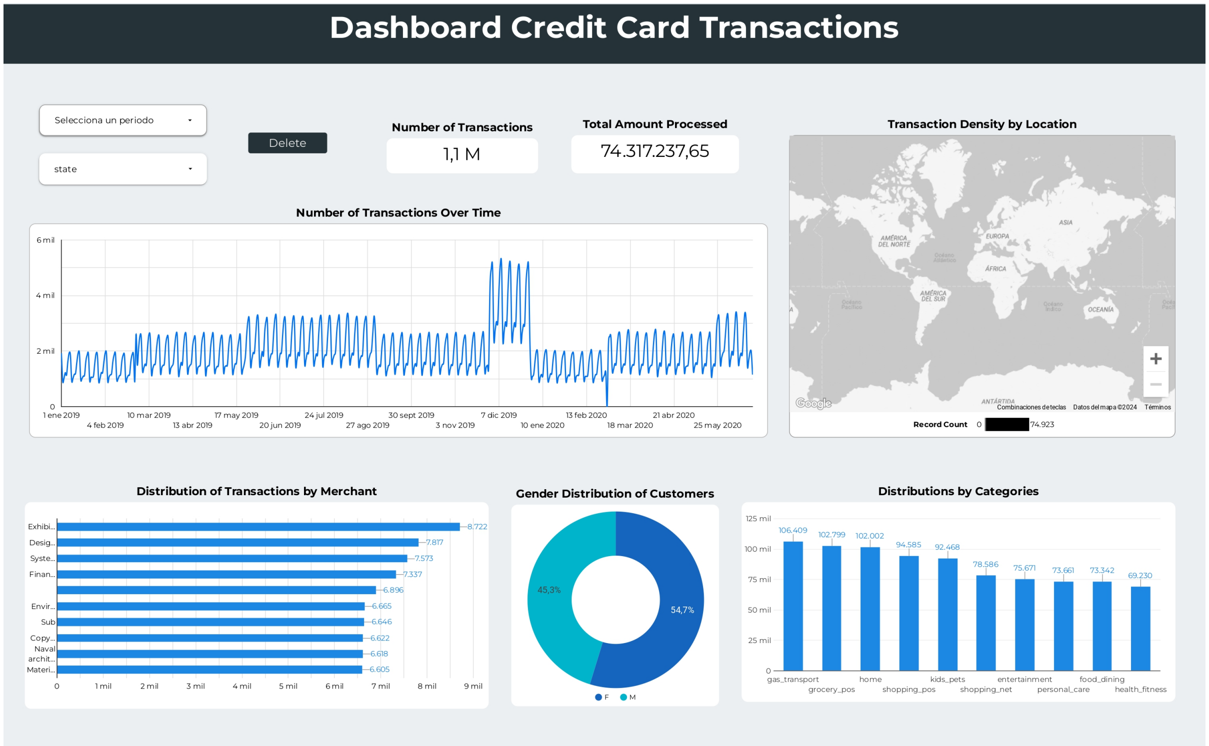


4. Data Visualization (ETL-Credit-Card-Transaction-Dashboard)

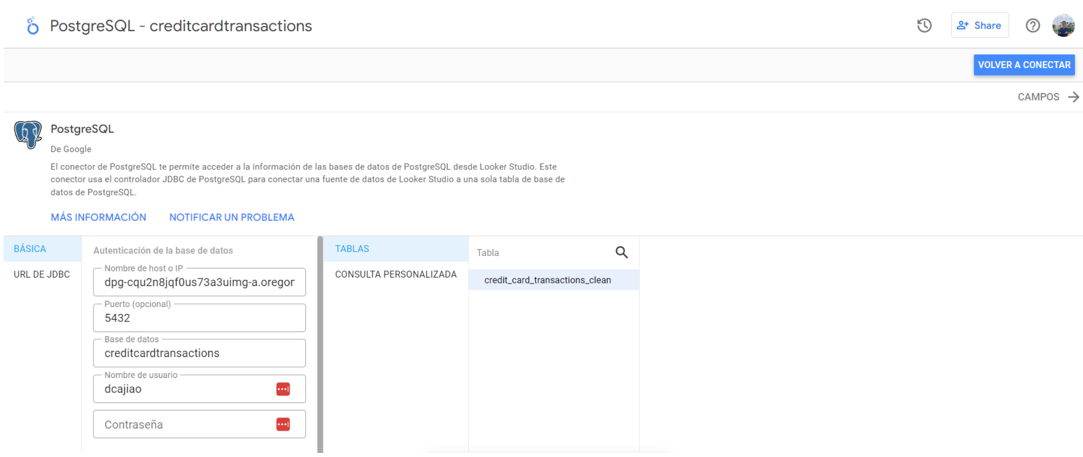
What was done?

The final step involved creating visualizations to meaningfully present the cleaned and processed data. These visualizations were designed to uncover trends, patterns, and insights that could guide decision-making.

- **Enhancement of Charts in Looker:** These visualizations were later enhanced in **Looker Studio**, where a more interactive and visually appealing dashboard was built.



- **Automatic Connection with the Cloud Database:** The advantage of using a cloud database, such as the instance on Render, allowed Looker to connect automatically, facilitating real-time updates to the dashboards as data was processed.



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5. Additional Relevant Aspects

PySQLSchema (`pysqlschema.py`)

One of the most notable components of this project was the use of `pysqlschema.py` , a custom script developed by DCajiao to programmatically manage SQL schemas using Python. This script was essential in ensuring that the database schema remained consistent throughout the project.

- **Schema Management:** `pysqlschema.py` enabled the dynamic creation, validation, and migration of database schemas. This was particularly useful during the data loading and cleaning phases, where the schema needed to be adjusted based on the characteristics of the data.
- **Automation:** The script automated various aspects of schema management, reducing the potential for human error and ensuring that schema changes were systematically applied across the entire database.

Relevance

- **Agile Development:** Thanks to the use of `pysqlschema.py`, the project benefited from an agile development process, where schema changes could be quickly implemented and tested without manual intervention.
- **Consistency and Integrity:** The script played a crucial role in maintaining the consistency and integrity of the database, ensuring that all data transformations adhered to the defined schema.
