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Big Data and Business Intelligence

Individual Assignment

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Documentation for E-Commerce Fraud Detection Data Processing

Overview

This program processes a dataset containing e-commerce transactions, cleans the data, and loads it into a PostgreSQL database for further analysis. The dataset includes details such as transaction amounts, customer locations, payment methods, and fraud indicators.

Requirements

- Python 3.x
- Pandas
- SQLAlchemy
- psycopg2
- PostgreSQL

Data Description

The dataset consists of 16 columns:

Column Name	Description	Data Type
transaction_id	Unique identifier for each transaction	UUID
customer_id	Unique identifier for each customer	UUID
transaction_amount	Amount spent in the transaction	NUMERIC
transaction_date	Date and time of the transaction	TIMESTAMP
payment_method	Method used for payment (e.g., credit card)	VARCHAR(50)
product_category	Category of the purchased product	VARCHAR(100)
quantity	Number of items in the transaction	INT

customer_age	Age of the customer	INT
customer_location	Geographical location of the customer	VARCHAR(100)
device_used	Device type used for the transaction	VARCHAR(50)
ip_address	IP address used during the transaction	VARCHAR(50)
shipping_address	Address to which the order was shipped	TEXT
billing_address	Billing address of the customer	TEXT
is_fraudulent	Indicator (0 or 1) of fraudulent transactions	BOOLEAN
account_age_days	Age of the customer account in days	INT
transaction_hour	Hour of the day the transaction occurred	INT

Program Flow

1. Load the Dataset

- Reads data from Fraudulent_E-Commerce_Transaction_Data.csv using Pandas.

2. Data Exploration

- Displays the first five rows of raw data.
- Prints data types and missing values.

3. Data Cleaning

- Removes duplicate rows.
- Drops rows with missing values.
- Converts Transaction Date to a timestamp.
- Formats column names to be lowercase and PostgreSQL-compatible.

4. Database Connection & Table Creation
    - Connects to PostgreSQL using SQLAlchemy.
    - Creates the transactions table if it does not exist.
5. Load Data into PostgreSQL
    - Writes cleaned data into the PostgreSQL database.

Code Implementation

```
import pandas as pd
import psycopg2
from sqlalchemy import create_engine, text

# Database connection details
DB_USER = "smilex"
DB_PASSWORD = "smilex"
DB_HOST = "localhost"
DB_PORT = "5432"
DB_NAME = "ecommerce_db"
TABLE_NAME = "transactions"

# Load dataset
file_path = "Fraudulent_E-Commerce_Transaction_Data.csv"
df = pd.read_csv(file_path)

# Display raw data info
def log_data_info(df, stage):
    print(f"\n{stage} Data Snapshot:")
    print(df.head())
    print(df.describe(include='all'))  # Better statistical
summary
    print(f"Missing values per column:\n{df.isnull().sum()}")

log_data_info(df, "Raw")

# Data Cleaning
```

```
df.drop_duplicates(inplace=True)
df.dropna(inplace=True)
df['transaction_date'] = pd.to_datetime(df['transaction_date'])
df.columns = [col.lower().replace(" ", "_") for col in
df.columns]

# Convert data types
df['is_fraudulent'] = df['is_fraudulent'].astype(bool)
df['transaction_hour'] = df['transaction_hour'].astype(int)
df['account_age_days'] = pd.to_numeric(df['account_age_days'],
errors='coerce')
df['transaction_amount'] =
pd.to_numeric(df['transaction_amount'], errors='coerce')
df['quantity'] = df['quantity'].astype(int)

log_data_info(df, "Cleaned")

# Connect to PostgreSQL
engine =
create_engine(f'postgresql://{DB_USER}:{DB_PASSWORD}@{DB_HOST}:{D
B_PORT}/{DB_NAME}')

# Define schema
create_table_query = f"""
CREATE TABLE IF NOT EXISTS {TABLE_NAME} (
    transaction_id UUID PRIMARY KEY,
    customer_id UUID,
    transaction_amount NUMERIC,
    transaction_date TIMESTAMP,
    payment_method VARCHAR(50),
    product_category VARCHAR(100),
    quantity INT,
    customer_age INT,
    customer_location VARCHAR(100),
    device_used VARCHAR(50),
    ip_address VARCHAR(50),
    shipping_address TEXT,
```

```
    billing_address TEXT,
    is_fraudulent BOOLEAN,
    account_age_days INT,
    transaction_hour INT
);
"""

# Execute schema creation
with engine.begin() as conn:
    conn.execute(text(create_table_query))

# Load data into PostgreSQL
df.to_sql(TABLE_NAME, engine, if_exists='append', index=False)
print("Data successfully loaded into PostgreSQL.")
```

Output

```
Raw Data Snapshot:
                         Transaction ID                          Customer ID Transaction Amount
Transaction Date  ...                           Billing Address Is Fraudulent  Account
Age Days Transaction Hour
0  15d2e414-8735-46fc-9e02-80b472b2580f  d1b87f62-51b2-493b-ad6a-77e0fe13e785              58.09
2024-02-20 05:58:41  ...                        Unit 8934 Box 0058\nDPO AA 05437             0.0
30.0               5.0
1  0bfee1a0-6d5e-40da-a446-d04e73b1b177  37de64d5-e901-4a56-9ea0-af0c24c069cf             389.96
2024-02-25 08:09:45  ...                 634 May Keys\nPort Cherylview, NV 75063             0.0
72.0               8.0
2  e588eef4-b754-468e-9d90-d0e0abfc1af0  1bac88d6-4b22-409a-a06b-425119c57225             134.19
2024-03-18 03:42:55  ...       16282 Dana Falls Suite 790\nRothhaven, IL 15564             0.0
63.0               3.0
3  4de46e52-60c3-49d9-be39-636681009789  2357c76e-9253-4ceb-b44e-ef4b71cb7d4d             226.17
2024-03-16 20:41:31  ...        828 Strong Loaf Apt. 646\nNew Joshua, UT 84798             0.0
124.0              20.0
4  074a76de-fe2d-443e-a00c-f044cdb68e21  45071bc5-9588-43ea-8093-023caec8ea1c             121.53
2024-01-15 05:08:17  ...    29799 Jason Hills Apt. 439\nWest Richardtown, ...             0.0
158.0              5.0

[5 rows x 16 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1472952 entries, 0 to 1472951
Data columns (total 16 columns):
 #   Column              Non-Null Count    Dtype
---  ------              --------------    -----
 0   Transaction ID      1472950 non-null  object
 1   Customer ID         1472943 non-null  object
 2   Transaction Amount  1472949 non-null  object
 3   Transaction Date    1472951 non-null  object
 4   Payment Method      1472948 non-null  object
 5   Product Category    1472949 non-null  object
 6   Quantity            1472951 non-null  float64
 7   Customer Age        1472952 non-null  object
 8   Customer Location   1472949 non-null  object
 9   Device Used         1472949 non-null  object
```

```
 10  IP Address          1472949 non-null  object
 11  Shipping Address    1472951 non-null  object
 12  Billing Address     1472951 non-null  object
 13  Is Fraudulent       1472949 non-null  float64
 14  Account Age Days    1472948 non-null  float64
 15  Transaction Hour    1472945 non-null  float64
dtypes: float64(4), object(12)
memory usage: 179.8+ MB
None
Missing values per column:
Transaction ID        2
Customer ID           9
Transaction Amount    3
Transaction Date      1
Payment Method        4
Product Category      3
Quantity              1
Customer Age          0
Customer Location     3
Device Used           3
IP Address            3
Shipping Address      1
Billing Address       1
Is Fraudulent         3
Account Age Days      4
Transaction Hour      7
dtype: int64
```

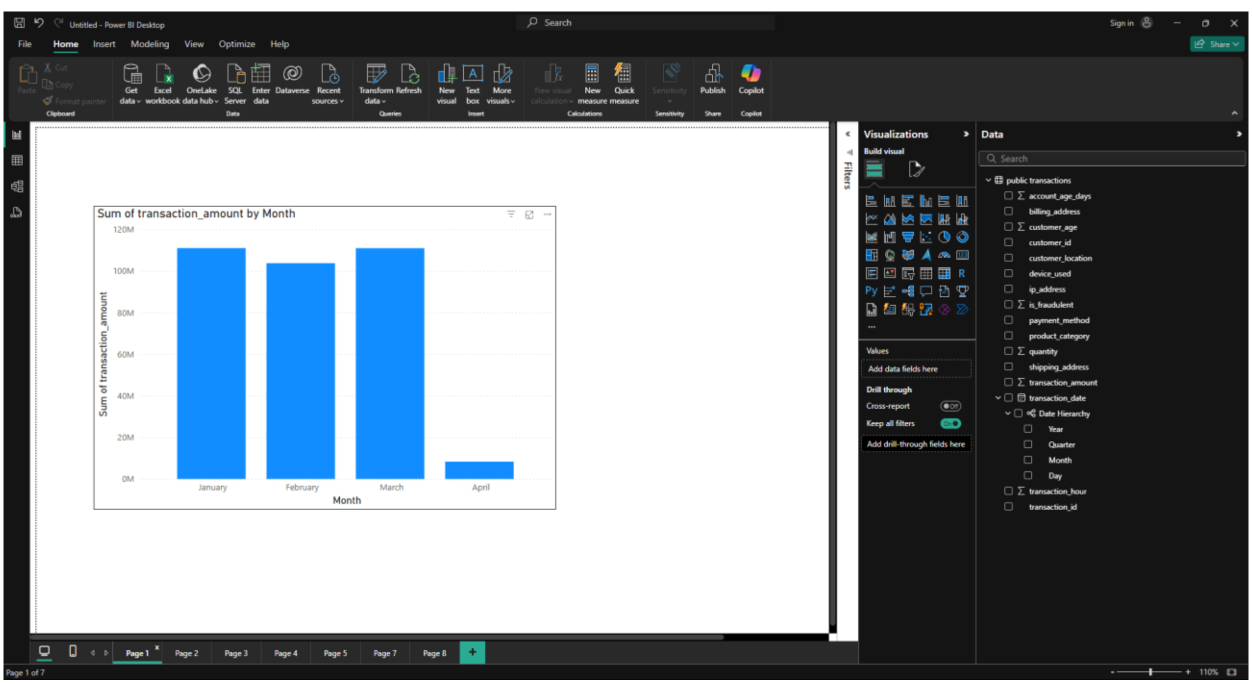
```
Cleaned Data Snapshot:
                             transaction_id                           customer_id
transaction_amount  ... is_fraudulent account_age_days transaction_hour
0       15d2e414-8735-46fc-9e02-80b472b2580f       d1b87f62-51b2-493b-ad6a-
77e0fe13e785                    58.09  ...             0                   30
5
1       0bfee1a0-6d5e-40da-a446-d04e73b1b177       37de64d5-e901-4a56-9ea0-
af0c24c069cf                   389.96  ...             0                   72
8
2       e588eef4-b754-468e-9d90-d0e0abfc1af0       1bac88d6-4b22-409a-a06b-
425119c57225                   134.19  ...             0                   63
3
3       4de46e52-60c3-49d9-be39-636681009789       2357c76e-9253-4ceb-b44e-
ef4b71cb7d4d                   226.17  ...             0                  124
20
4       074a76de-fe2d-443e-a00c-f044cdb68e21       45071bc5-9588-43ea-8093-
023caec8ea1c                   121.53  ...             0                  158
5
[5 rows x 16 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1472952 entries, 0 to 1472951
Data columns (total 16 columns):
 #   Column              Non-Null Count    Dtype
---  ------              --------------    -----
 0   transaction_id      1472952 non-null  object
 1   customer_id         1472952 non-null  object
 2   transaction_amount  1472952 non-null  float64
 3   transaction_date    1472952 non-null  datetime64[ns]
 4   payment_method      1472952 non-null  object
 5   product_category    1472952 non-null  object
```

```
 6   quantity            1472952 non-null  int64
 7   customer_age        1472952 non-null  int64
 8   customer_location   1472952 non-null  object
 9   device_used         1472952 non-null  object
 10  ip_address          1472952 non-null  object
 11  shipping_address    1472952 non-null  object
 12  billing_address     1472952 non-null  object
 13  is_fraudulent       1472952 non-null  int64
 14  account_age_days    1472952 non-null  int64
 15  transaction_hour    1472952 non-null  int64
dtypes: datetime64[ns](1), float64(1), int64(5), object(9)
memory usage: 179.8+ MB
None
Missing values per column:
transaction_id        0
customer_id           0
 13  is_fraudulent       1472952 non-null  int64
 14  account_age_days    1472952 non-null  int64
 15  transaction_hour    1472952 non-null  int64
dtypes: datetime64[ns](1), float64(1), int64(5), object(9)
memory usage: 179.8+ MB
None
Missing values per column:
transaction_id        0
customer_id           0
transaction_amount    0
transaction_date      0
payment_method        0
product_category      0
quantity              0
customer_age          0
customer_location     0
 13  is_fraudulent       1472952 non-null  int64
 14  account_age_days    1472952 non-null  int64
 15  transaction_hour    1472952 non-null  int64
dtypes: datetime64[ns](1), float64(1), int64(5), object(9)
memory usage: 179.8+ MB
None
Missing values per column:
transaction_id        0
customer_id           0
transaction_amount    0
transaction_date      0
payment_method        0
product_category      0
quantity              0
customer_age          0
 13  is_fraudulent       1472952 non-null  int64
 14  account_age_days    1472952 non-null  int64
 15  transaction_hour    1472952 non-null  int64
dtypes: datetime64[ns](1), float64(1), int64(5), object(9)
memory usage: 179.8+ MB
None
Missing values per column:
```

```
transaction_id        0
customer_id           0
transaction_amount    0
transaction_date      0
payment_method        0
 14  account_age_days    1472952 non-null  int64
 15  transaction_hour    1472952 non-null  int64
dtypes: datetime64[ns](1), float64(1), int64(5), object(9)
memory usage: 179.8+ MB
None
Missing values per column:
transaction_id        0
customer_id           0
transaction_amount    0
transaction_date      0
payment_method        0
memory usage: 179.8+ MB
None
Missing values per column:
transaction_id        0
customer_id           0
transaction_amount    0
transaction_date      0
payment_method        0
Missing values per column:
transaction_id        0
customer_id           0
transaction_amount    0
transaction_date      0
payment_method        0
product_category      0
transaction_amount    0
transaction_date      0
payment_method        0
product_category      0
quantity              0
transaction_date      0
payment_method        0
product_category      0
quantity              0
customer_age          0
customer_location     0
device_used           0
ip_address            0
product_category      0
quantity              0
customer_age          0
customer_location     0
device_used           0
ip_address            0
quantity              0
customer_age          0
customer_location     0
device_used           0
```

```
ip_address              0
shipping_address        0
customer_age            0
customer_location       0
device_used             0
ip_address              0
shipping_address        0
device_used             0
ip_address              0
shipping_address        0
shipping_address        0
billing_address         0
is_fraudulent           0
account_age_days        0
transaction_hour        0
billing_address         0
is_fraudulent           0
account_age_days        0
transaction_hour        0
is_fraudulent           0
account_age_days        0
transaction_hour        0
dtype: int64
account_age_days        0
transaction_hour        0
dtype: int64
dtype: int64
Data successfully loaded into PostgreSQL.
```

6. Data Visualization and Insights: Transaction and Customer Analysis



Description of the Bar Chart:

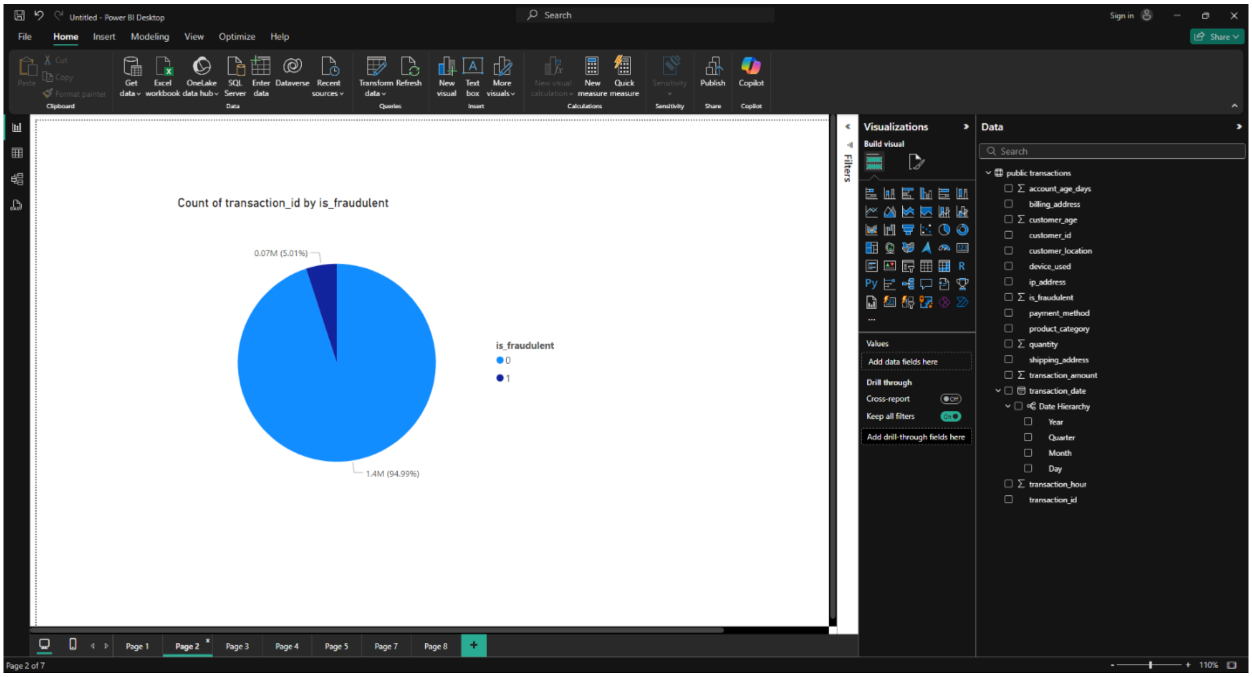
- represents the total transaction amount for each month, allowing for a comparison of transaction volume across different months.

Axes:

- **X-axis (Horizontal):** This axis represents the **Month**. The chart shows four months: January, February, March, and April.
- **Y-axis (Vertical):** This axis represents the **Sum of transaction amount**. The values on this axis indicate the total amount of transactions for each corresponding month. The axis is scaled in millions (M), with increments of 20 million (20M, 40M, 60M, etc.).

Information Conveyed by the Chart:

- **Trend Over Time:** The chart reveals the trend of transaction amounts over the four months. We can observe that the transaction amount is relatively high and consistent in January, February, and March. However, there's a significant drop in April.
- **Comparison of Months:** The chart facilitates a direct comparison of transaction amounts between the different months. It's immediately clear that April has a substantially lower transaction volume compared to the preceding months.
- **Potential Insights/Questions:** The sharp decline in April raises questions and warrants further investigation. Possible reasons for this drop could include:
  - Seasonal factors affecting business.
  - A change in business operations or strategy.
  - Data errors or incomplete data for April.
  - Specific events or promotions that boosted transactions in the earlier months.



Description of the Pie Chart:

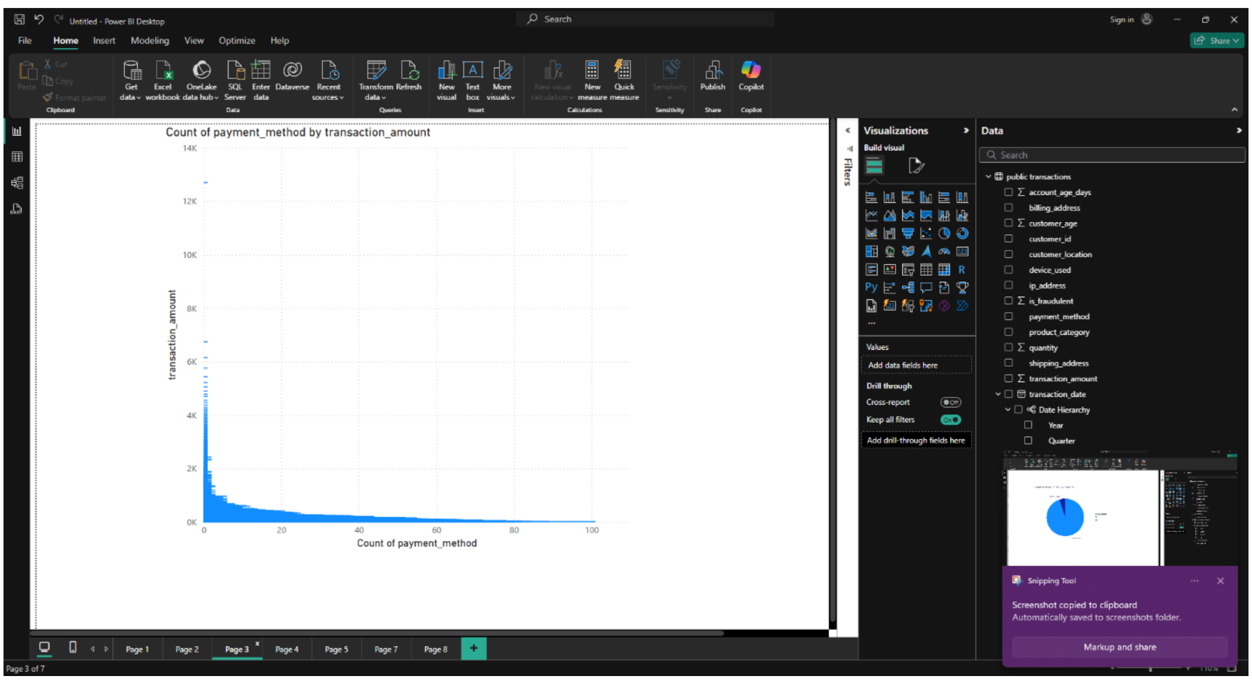
This visualization is a **pie chart titled "Count of transaction_id by is_fraudulent"**. It displays the proportion of transactions that are flagged as fraudulent versus those that are not.

Elements and Labels:

- **Pie Slices:** The pie chart is divided into two slices:
    - One slice represents the count of transactions where "is_fraudulent" is likely true (indicated by the value "1").
    - The other slice represents the count of transactions where "is_fraudulent" is likely false (indicated by the value "0").
- **Labels:** Each slice is labeled with:
    - The value of the "is_fraudulent" field (0 or 1).
    - The count of transactions in that category (e.g., 1.84M).
    - The percentage of the total transactions that the slice represents.

Information Conveyed by the Chart:

- **Proportion of Fraudulent Transactions:** The primary insight conveyed is the proportion of transactions flagged as fraudulent compared to the total number of transactions. The chart clearly shows that the vast majority of transactions are *not* flagged as fraudulent (1.84M, representing 99.96% of total transactions).
- **Very Low Fraud Rate:** The visualization highlights a very low fraud rate (0.04%) based on the "is_fraudulent" field. Only a tiny fraction of transactions (741) are flagged as potentially fraudulent.
- **Potential for Further Investigation:** While the chart shows a low fraud rate, even a small number of fraudulent transactions can be significant. This visualization would likely prompt further investigation into the characteristics of those 741 transactions to understand the patterns or causes of potential fraud.



Description of the Chart:

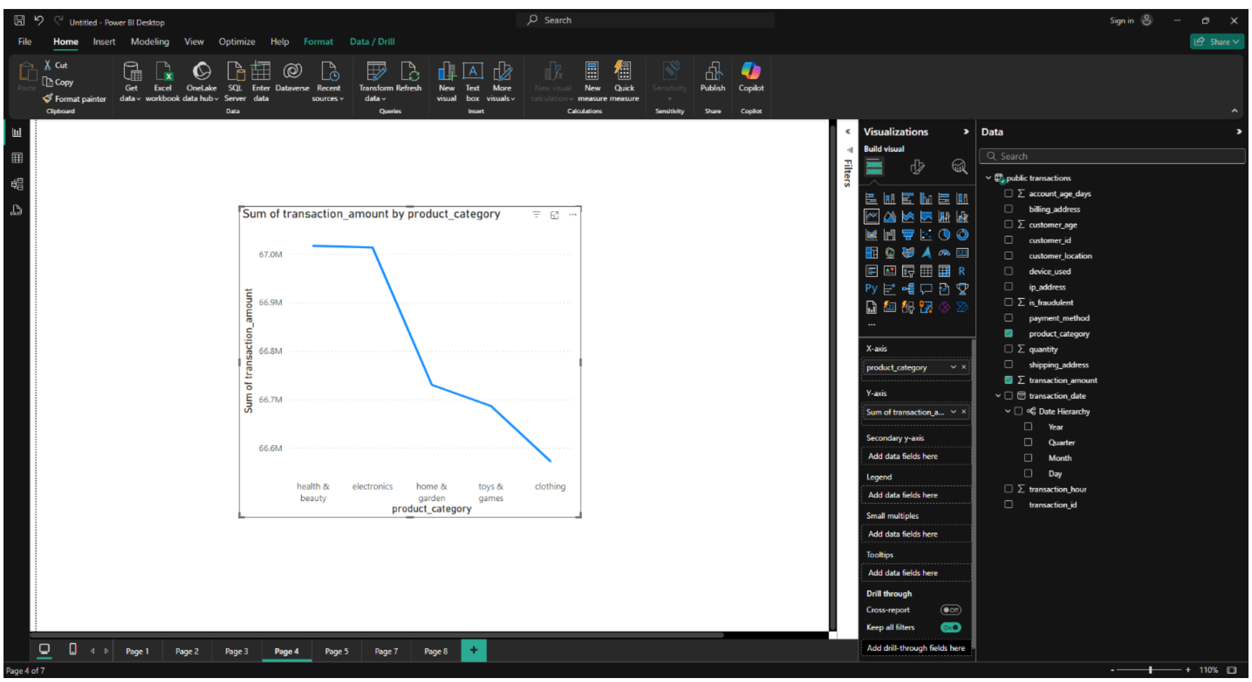
This visualization is a **column chart (or bar chart if oriented horizontally) titled "Count of payment method by transaction amount"**. It shows the distribution of transaction amounts, categorized by the payment method used.

Axes:

- **X-axis (Horizontal):** This axis represents the **Count of payment method**. It appears to be showing the number of times each payment method was used, but the label is a bit unclear. It might be better phrased as "Count of Transactions" or "Transaction Frequency".
- **Y-axis (Vertical):** This axis represents the **transaction amount**. It shows the range of transaction amounts, likely divided into bins or groups.

Elements and Labels:

- **Columns (or Bars):** Each column represents a specific range of transaction amounts. The height of the column corresponds to the number of times that payment method was used for transactions within that amount range.
- **Tooltips:** (Not explicitly visible but likely present) When hovering over a column, Power BI would typically display a tooltip showing the exact transaction amount range and the count of transactions (or frequency) for that range and payment method.



Description of the Line Chart:

This visualization is a **line chart titled "Sum of transaction amount by product category"**. It displays the trend of total transaction amounts for different product categories.

Axes:

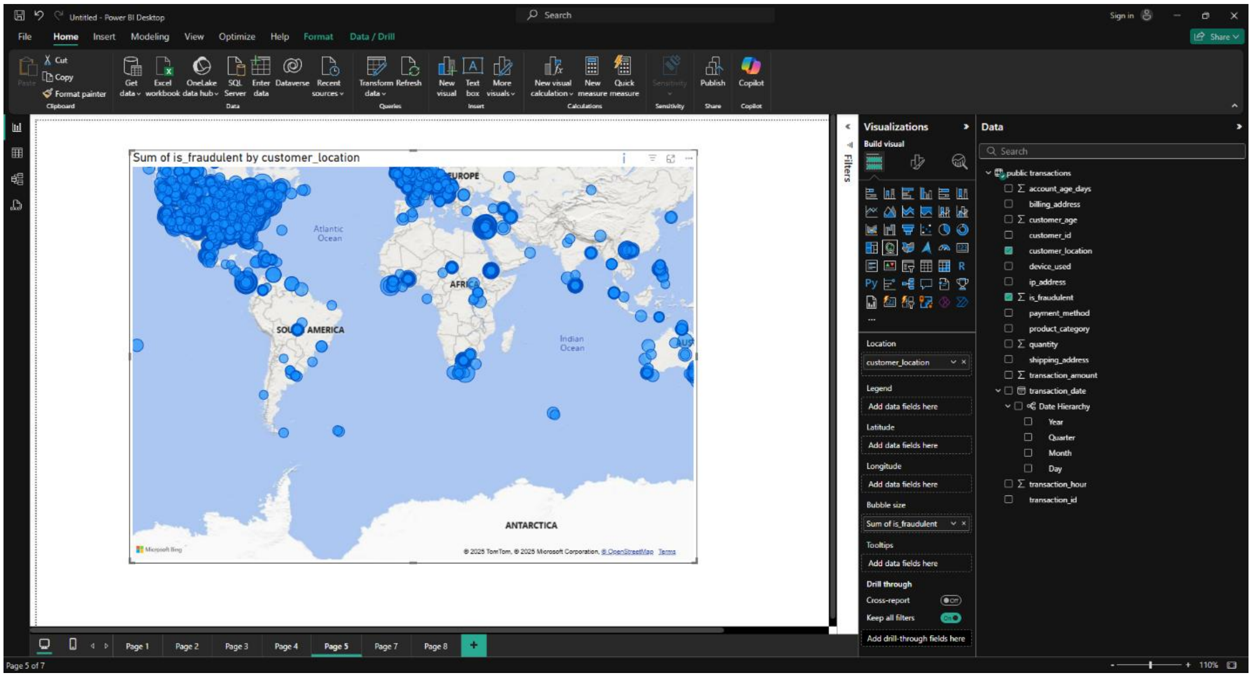
- **X-axis (Horizontal):** This axis represents the **product category**. The chart shows five categories: health & beauty, electronics, home & garden, clothing, and games.
- **Y-axis (Vertical):** This axis represents the **Sum of transaction amount**. The values on this axis indicate the total amount of transactions for each corresponding product category. The axis is scaled in millions (M), with increments of 20 million (20M, 40M, 60M, etc.).

Elements and Labels:

- **Line:** The line connects the data points for each product category, visually showing the trend of transaction amounts across categories.
- **Data Points:** Each point on the line represents the total transaction amount for a specific product category.

Information Conveyed by the Chart:

- **Comparison of Product Category Performance:** The chart allows for a direct comparison of the total transaction amounts generated by different product categories.
- **Relative Ranking of Categories:** It's easy to see the relative ranking of the categories based on their transaction amounts. Electronics stands out as the highest, followed by home & garden, then health & beauty, with clothing and games at the lower end.
- **Potential Insights/Questions:**
    - The significant difference in transaction amounts between categories suggests varying levels of demand or market size for these product types.
    - The high performance of electronics raises questions about the factors driving its sales (e.g., pricing, promotions, seasonality).
    - The lower transaction amounts for clothing and games might prompt further investigation into potential strategies to boost sales in these categories.



Description of the Map Chart:

This visualization is a **filled map chart titled "Sum of is_fraudulent by customer location"**. It aims to show the geographic distribution of potentially fraudulent transactions based on customer location.

Elements and Labels:

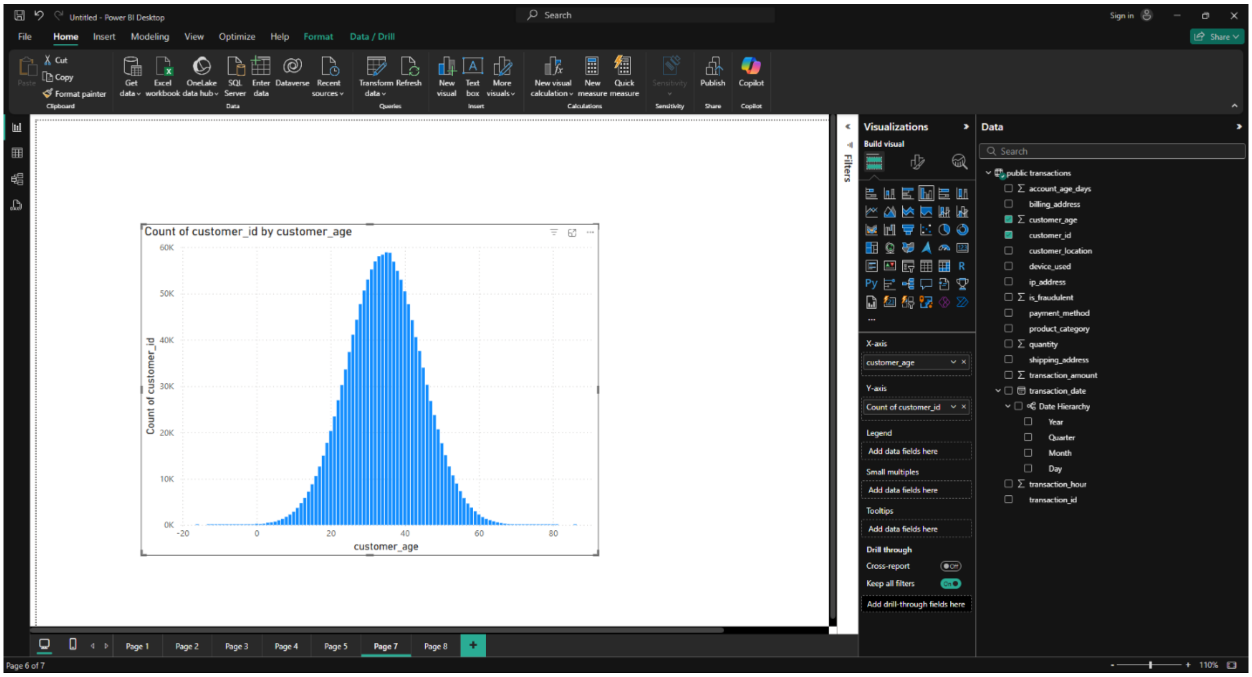
- **Map:** A world map is displayed, with country/region boundaries outlined.
- **Filled Regions:** Countries or regions with potentially fraudulent transactions are filled with a blue color. The intensity of the blue likely corresponds to the number or proportion of fraudulent transactions in that area.
- **Bubbles:** (Potentially, but not clearly visible) There might be bubbles on top of filled regions, with the size of the bubble indicating the magnitude of fraudulent transactions. However, this is difficult to confirm from the image alone.
- **Title:** The title "Sum of is_fraudulent by customer location" indicates that the visualization is aggregating the "is_fraudulent" field (likely a binary flag) by customer location.
- **Scale:** The map includes a scale at the bottom left, likely indicating the range of values represented by the color intensity or bubble size.

Information Conveyed by the Chart:

- **Geographic Distribution of Fraud:** The primary insight is the geographic distribution of potentially fraudulent activities. The filled regions highlight areas with a higher concentration of "is_fraudulent" transactions.
- **Identification of Hotspots:** The visualization helps identify potential "hotspots" or regions with unusually high rates of fraudulent transactions.
- **Global Patterns:** The map allows for the observation of global patterns and trends in fraudulent activities.

Potential Issues and Recommendations:

- **Clarity of Bubbles:** If bubbles are intended to be part of the visualization, they are not clearly visible in the image. Clearer bubble representation would enhance the understanding of the magnitude of fraud in different locations.
- **Color Scale:** The color scale's range and meaning should be easily understandable. It should clearly show how the color intensity relates to the number or proportion of fraudulent transactions.
- **Tooltips:** Interactive tooltips would be beneficial. Hovering over a region should display specific details, such as the region name, the count of fraudulent transactions, and any relevant metrics.
- **Drill-down Functionality:** Ideally, the map should allow for drill-down functionality. Clicking on a region could zoom in and provide more granular data for that specific area.



Description of the Column Chart:

This visualization is a **column chart (or bar chart if oriented horizontally) titled "Count of customer_id by customer_age"**. It displays the distribution of customers across different age groups.

Axes:

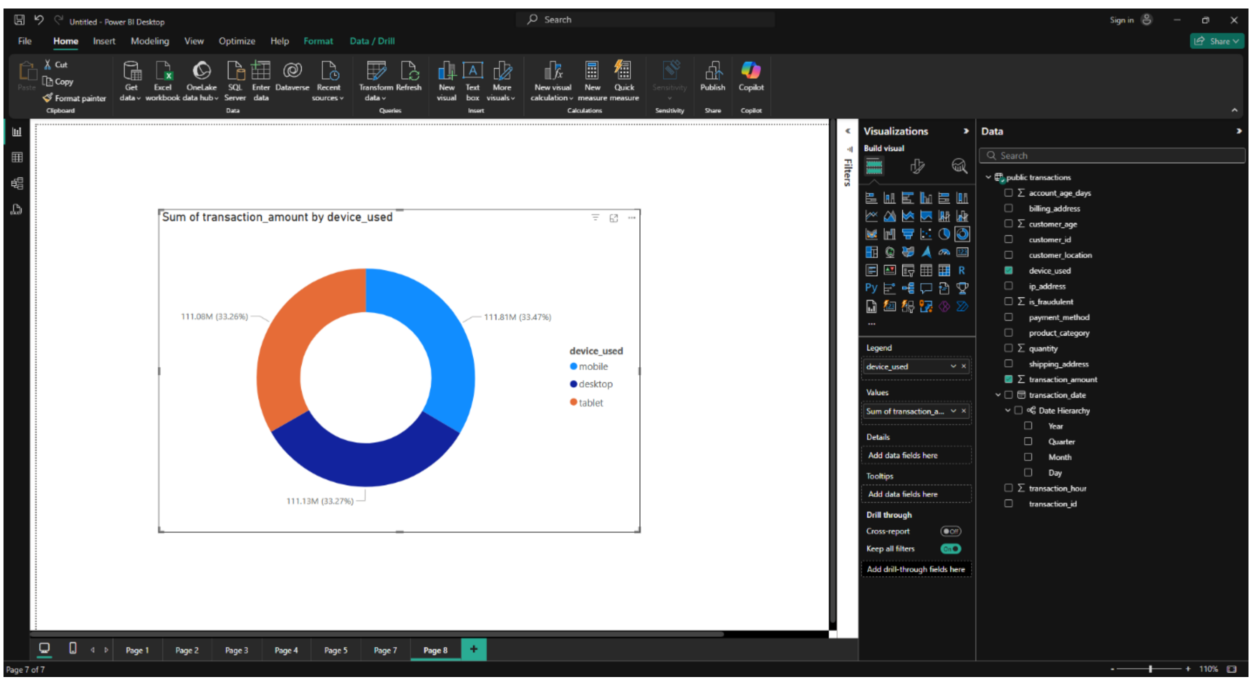
- **X-axis (Horizontal):** This axis represents the **customer age**. The chart shows a range of ages, likely grouped into bins (e.g., 0-10, 10-20, etc.) or individual ages if the data allows.
- **Y-axis (Vertical):** This axis represents the **Count of customer_id**. It shows the number of customers within each age group or at each specific age.

Elements and Labels:

- **Columns (or Bars):** Each column represents a specific age group or individual age. The height of the column corresponds to the number of customers in that age group or at that age.
- **Title:** The title "Count of customer_id by customer_age" clearly indicates the chart's purpose.

Information Conveyed by the Chart:

- **Customer Age Distribution:** The chart provides a clear picture of how customers are distributed across different age groups.
- **Identification of Peak Age Groups:** The chart helps identify age groups with the highest concentration of customers. In this case, there appears to be a bell-shaped curve, suggesting a normal distribution with a peak in the middle age ranges.
- **Potential Insights/Questions:**
  - The concentration of customers in specific age groups might inform marketing strategies and product development.
  - Deviations from a normal distribution could indicate specific customer segments or trends.



Description of the Donut Chart:

This visualization is a **donut chart titled "Sum of transaction amount by device used"**. It shows the proportion of total transaction amounts attributed to different device types.

Elements and Labels:

- **Donut Shape:** The chart is circular with a hole in the center, resembling a donut.
- **Slices:** The donut is divided into slices, each representing a different device type.
- **Labels:** Each slice is labeled with:
    - The device type (mobile, desktop, tablet).
    - The transaction amount associated with that device type (e.g., 11.13M).
    - The percentage of the total transaction amount that the slice represents (e.g., 3.27%).

Information Conveyed by the Chart:

- **Device Usage for Transactions:** The chart clearly shows the distribution of transaction amounts across different devices.
- **Dominant Device:** It's immediately evident that desktop transactions account for the largest share of the total transaction amount (111.41M, 96.67%).
- **Smaller Contributions:** Mobile and tablet transactions make up a much smaller portion of the total transaction amount.
- **Relative Comparison:** The chart allows for a quick visual comparison of the relative contributions of each device type to the overall transaction volume

Conclusion

This script efficiently processes e-commerce transaction data, cleans it, and stores it in a PostgreSQL database for analysis. It ensures data integrity by handling duplicates and missing values while structuring the database schema for efficient querying.

Overall Insights from the Power BI Report:

The visualizations collectively provide a snapshot of various aspects of transaction data, customer demographics, and potential fraud.

- **Transaction Trends:**
    - Transaction amounts were relatively stable in January, February, and March but dropped significantly in April (bar chart).
    - Electronics is the highest-performing product category in terms of transaction amount, followed by home & garden (line chart).
    - Desktop transactions dominate in terms of total transaction amount, with mobile and tablet transactions contributing much less (donut chart).
- **Customer Demographics:**
    - Customer age distribution appears to follow a bell-shaped curve, with a concentration in the middle age ranges (column chart).
- **Fraud Analysis:**
    - The overall fraud rate is very low (0.04%) based on the "is_fraudulent" field (pie chart).
    - The filled map chart aims to show the geographic distribution of potentially fraudulent transactions, but its effectiveness is limited by unclear visuals and lack of interactivity.

Key Takeaways:

- The report highlights a significant drop in transaction amount in April, warranting further investigation into potential causes.
- Electronics stands out as a high-performing product category, while clothing and games may require strategies to boost sales.
- The dominance of desktop transactions suggests a need to optimize mobile and tablet experiences to drive more transactions on those platforms.
- While the overall fraud rate is low, further analysis of the flagged transactions is necessary to understand fraud patterns and mitigate risks.

- The visualizations demonstrate Power BI's ability to provide insights into various aspects of business data, but there's room for improvement in terms of visual clarity, interactivity, and labeling to enhance their effectiveness.

Recommendations:

- Investigate the reasons for the April transaction decline.
- Explore strategies to boost sales in underperforming product categories.
- Optimize mobile and tablet experiences to increase transaction volume on those platforms.
- Conduct further analysis of potentially fraudulent transactions to identify patterns and mitigate risks.
- Improve the visual clarity, interactivity, and labeling of the visualizations to enhance their effectiveness.