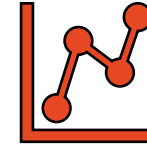


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# Brazilian E-commerce Data Analytics Reporting

*Presented By: Ganna Hassan*

# INTRODUCTION



➡ **This project focuses on analyzing raw Brazilian e-commerce data to generate actionable insights. The main goal is to create a smart visualization dashboard that helps businesses understand online retail dynamics in Brazil. The project addresses challenges like unclear data patterns and regional disparities in sales and customer behavior.**

A person in a dark suit is holding a tablet that displays various business analytics, including line graphs, bar charts, and tables of data. The background is dark and out of focus.

# Objectives of the Analysis

- ☐ *Understand customer purchasing behavior.*
- ☐ *Identify top-selling product categories and regions.*
- ☐ *Analyze payment preferences and delivery performance.*
- ☐ *Calculate Customer Lifetime Value (CLV).*
- ☐ *Detect high-return product categories.*
- ☐ *Offer insights to improve decision-making for e-commerce stakeholders*

# Dataset Description

- Data Source: Brazilian E-commerce Public Dataset
- Tables Involved:
  - **Customers**: Customer IDs, location info.
- 2. **Orders**: Order lifecycle details.
- 3. **Order Items**: Product, seller, price, shipping info.
- 4. **Order Payments**: Payment method and value.
- 5. **Order Reviews**: Customer satisfaction scores.
- 6. **Products**: Product category details.
- 7. **Sellers**: Seller location and IDs.
- 8. **Geolocation**: Mapping ZIP codes to cities/states.
- Data Type: Relational, structured in CSV
- Format Storage: PostgreSQL.
- Access: REST API (Flask) with React frontend.





## Data Cleaning & Preparation

### Steps Taken

- ✓ Removed duplicate
- ✓ Rows Handled missing values (e.g., imputing ZIP codes using city averages).
- ✓ Standardized formats (e.g., date fields, category name normalization from Portuguese to English).
- ✓ Converted data types (e.g., strings to datetime).
- ✓ Corrected inaccurate or inconsistent entries.
- ✓ Detected and managed outliers.
- ✓ Applied normalization/scaling for analysis.
- ✓ Tools used: Python (Pandas), SQL.

# Relations Between Data Points

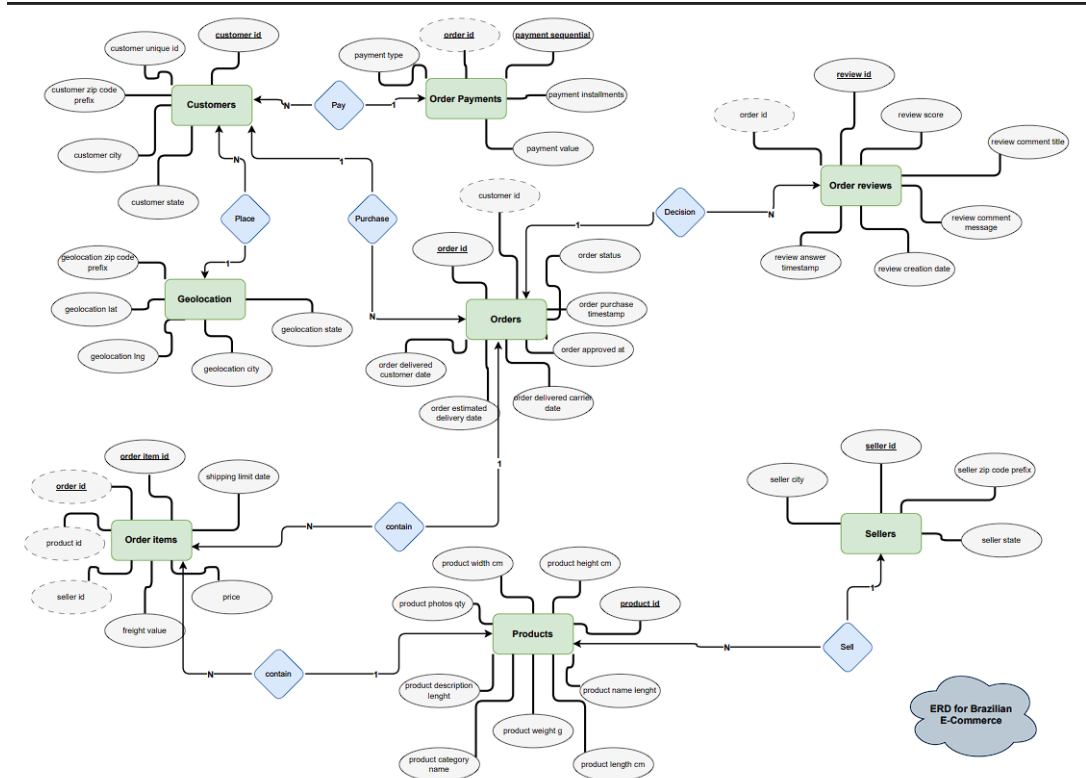


Table Name	Key	Relationship
Customers	Customer ID (PK)	Orders, Order payment, Geolocation (1: N)
Orders	Order ID (PK) Customer ID (FK)	Order Item, Order Review, Customers (1: N)
Order Items	Order Item ID (PK) Order ID (FK)	Orders, Products (1: N)
Order Review	Review ID (PK) Order ID (FK)	Orders (1: N)
Order Payment	Sequential Payment (PK) Order ID (FK)	Customers (1: N)
Geolocation	NONE	Customers (1: N)
Products	Product ID (PK)	Sellers, Order Items (1: N)
Sellers	Seller ID (PK)	Products (1: N)



# Exploratory Data Analysis

# Exploratory Data Analysis (EDA)

```
32 --6-Revenue by product category:
33 SELECT p.product_category_name,
34 SUM(oi.price + oi.freight_value) AS category_revenue
35 FROM order_items oi
36 JOIN products p ON oi.product_id = p.product_id
37 JOIN orders o ON oi.order_id = o.order_id
38 WHERE o.order_status = 'delivered'
39 GROUP BY p.product_category_name
40 ORDER BY category_revenue DESC
```

```
--7-Revenue Per seller:
SELECT s.seller_id, SUM(oi.price + oi.freight_value) AS seller_revenue
FROM order_items oi
JOIN sellers s ON oi.seller_id = s.seller_id
JOIN orders o ON oi.order_id = o.order_id
WHERE o.order_status = 'delivered'
GROUP BY s.seller_id
ORDER BY seller_revenue DESC;
```

```
--8-Revenue per customer:
SELECT o.customer_id, SUM(oi.price + oi.freight_value) AS customer_revenue
FROM order_items oi
JOIN orders o ON oi.order_id = o.order_id
WHERE o.order_status = 'delivered'
GROUP BY o.customer_id
ORDER BY customer_revenue DESC;
```

```
95 --10- Monthly Revenue forecast:
96 WITH MonthlyRevenue AS (
97     SELECT
98         YEAR(o.order_purchase_timestamp) AS Year,
99         MONTH(o.order_purchase_timestamp) AS Month,
100         SUM(oi.price + oi.freight_value) AS MonthlyRevenue
101     FROM orders o
102     JOIN order_items oi ON o.order_id = oi.order_id
103     WHERE o.order_status = 'delivered'
104     GROUP BY YEAR(o.order_purchase_timestamp), MONTH(o.order_purchase_timestamp)
105 )
106 SELECT Year, Month, MonthlyRevenue,
107     AVG(MonthlyRevenue) OVER (ORDER BY Year, Month ROWS BETWEEN 2 PRECEDING AND CURRENT ROW) AS MovingAvg3Months
108 from MonthlyRevenue
109
110 --11- Number of unique customers:
111 SELECT COUNT(DISTINCT customer_id) AS unique_customers
112 FROM customers
113 --OR
114 SELECT
115     COUNT(DISTINCT COALESCE(customer_id, 'MISSING_ID')) AS unique_customers
116 FROM customers
```



# Exploratory Data Analysis (EDA)

Performed using SQL and Python :Overviewed distributions of sales, payments, and customer locations.

Plotted frequency charts for: Order statuses.

Payment types Review scores.

Regional order distributions.

Time series plots for peak purchase times.

Sample Of KPIs : Revenue  
per product category By  
SQL



	product_category_name	category_revenue	revenue_percentage
1	health_beauty	1412089.53	9.16
2	watches_gifts	1264333.12	8.2
3	bed_bath_table	1225209.26	7.95
4	sports_leisure	1118256.91	7.25
5	computers_accessories	1032723.77	6.7
6	furniture_decor	880329.9199999994	5.71
7	housewares	758392.2499999995	4.92
8	cool_stuff	691680.89	4.49
9	auto	669454.7499999999	4.34
10	garden_tools	567145.68	3.68
11	toys	547061.0599999999	3.55
12	baby	466727.65	3.03
13	perfumery	443171.6300000003	2.87
14	telephony	379202.6200000005	2.46
15	office_furniture	335211.36	2.17
16	stationery	269575.0500000001	1.75
17	pet_shop	250614.2	1.63
18	computers	228349.76	1.48
19	#N/A	203353.8400000001	1.32
20	musical_instruments	202187.12	1.31

# Exploratory Data Analysis (EDA)

Using Python

```
#1.Total Revenue (for delivered orders)
delivered = order_data[order_data["order_status"] == "delivered"]
total_revenue = (delivered["price"] + delivered["freight_value"]).sum()
print("Total Revenue:", round(total_revenue, 2))
```

```
#11.Number of Unique Customers
customer_orders = pd.merge(orders, customers, on="customer_id", how="left")
delivered_customers = customer_orders[customer_orders["order_status"] == "delivered"]
#Total Number of Unique Customers
total_customers = customers["customer_id"].nunique()
print("Total Unique Customers:", total_customers)
```

(Late Delivery Rate: 7.91%)

```
#29.Popular Payment Methods
payments = pd.read_csv("olist_order_payments_dataset.csv")
orders_payments = pd.merge(orders, payments, on="order_id", how="left")

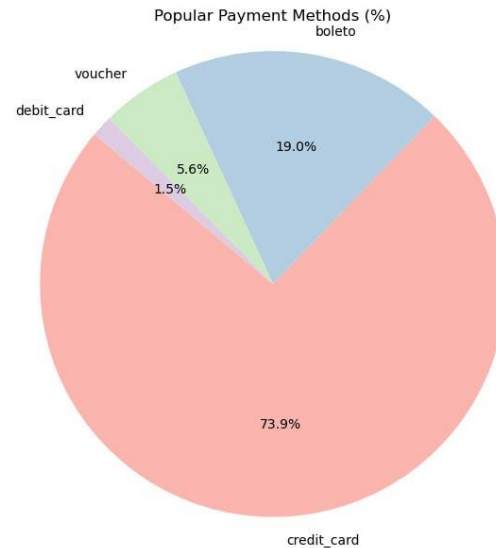
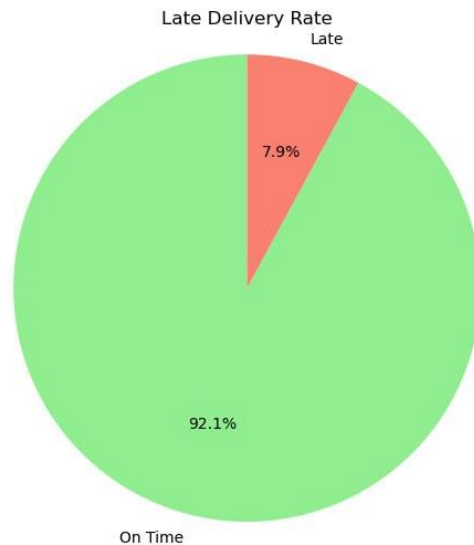
payment_counts = orders_payments['payment_type'].value_counts()
payment_percentages = (payment_counts / payment_counts.sum()) * 100
print(payment_percentages.round(2).astype(str) + " %")

payment_counts = orders_payments['payment_type'].value_counts()
payment_percentages = (payment_counts / payment_counts.sum()) * 100
payment_percentages_filtered = payment_percentages[payment_percentages.index != 'not_defined']
plt.figure(figsize=(8, 6))
plt.pie(payment_percentages_filtered,
        labels=payment_percentages_filtered.index,
        autopct='%1.1f%%',
        startangle=140,
        colors=plt.cm.Pastel1.colors)
plt.title("Popular Payment Methods (%)")
plt.axis('equal')
plt.tight_layout()
plt.show()
```

(Total Revenue: 15419773.75)

# Exploratory Data Analysis (EDA)

*Samples of Visualization Using Python*



(credit\_card 12542084.19)

(boleto 2869361.27)

(voucher 379436.87)

(debit\_card 217989.79)

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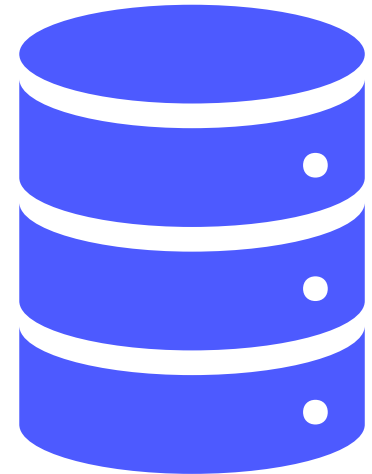
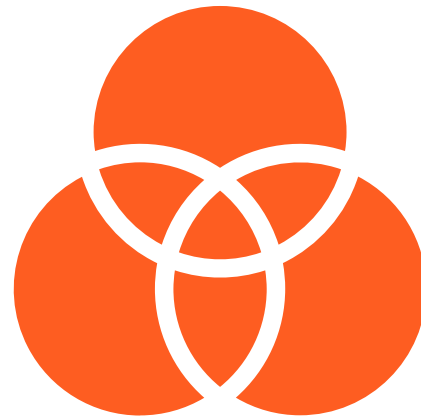
# Deep-Dive Analysis

- State-Level Sales: Mapped sales by region using geolocation.
- Top Categories: Ranked product categories by revenue.
- Payment Analysis: Identified most common payment methods.
- Delivery Performance: Evaluated shipping delays and average delivery times by state.
- Customer CLV: Analyzed which customers contributed the most revenue.
- Return Rates: Flagged categories with high return frequencies.
- Temporal Trends: Tracked weekly/monthly sales patterns.



# Key Insights

- Southeast Brazil leads in both order volume and revenue.
- Electronics and fashion are top-performing product categories.
- "Credit card" is the dominant payment method.
- Delivery delays occur more frequently in northern regions.
- Customers with high purchase frequency often give higher review scores.
- Return rates were highest in fashion and furniture categories.

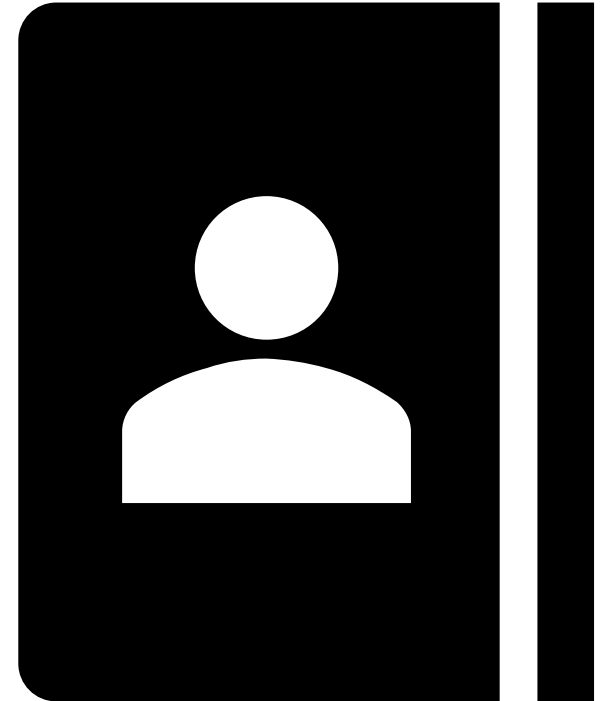




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# Recommendations

- Optimize Logistics in underperforming delivery regions.
- Focus Promotions on high-CLV customers.
- Improve Return Policies in high-return categories.
- Enhance Seller Dashboards with product-level performance alerts.
- Introduce Loyalty Programs for repeat buyers.



# Deliverables

- Dataset (CSV file)
- A comprehensive description that effectively communicates the details of your project.
- A ZIP File containing your Project Source Code. (python, sql)
- A URL to your Live application, system, or dashboard after deployment. (Tableau public)
- Project Documentation (project design, wireframe, model, visualizations.)



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# Conclusion



**This project successfully transformed complex Brazilian e-commerce data into a set of meaningful dashboards and reports. It provides business users with an interactive platform to explore trends, address customer needs, and optimize operations.**





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# References

- Python (Pandas)
- Microsoft SQL Server
- Tableau & Power BI
- Google Cloud Platform
- GitHub for version control
- Collaboration methods (e.g., communication tools, agile methodologies)
- ? Used GitHub for version control.
- ? Held weekly syncs via Google Meet.