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From Data to Strategy: Customer Segmentation and Insights for Olist

Statistical Insights into Customer Behavior: A Case Study of Olist

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**Research Question**

Olist is a Brazilian e-commerce platform that connects small and medium-sized businesses (SMBs) to major online marketplaces like Amazon, Mercado Libre, and others (Unicorn Companies in Brazil, 2024). This study will utilize K-Means clustering to segment customers based on behavioral data, such as Average Order Value (AOV), and apply ANOVA to evaluate statistical differences across the identified segments (Kashwan & Velu, 2013). In the context of the Olist platform, analyzing differences in AOV among customer segments provides actionable insights into purchasing behavior, enabling more targeted marketing efforts and optimized resource allocation (Understanding and Improving Average Order Value (AOV), n.d.).

The research question, "Are there significant differences in average order value across customer segments within the Olist e-commerce platform?" is justified by the need for businesses to better understand customer behavior to improve personalized marketing strategies and enhance customer retention. The hypotheses are as follows:

* **Null Hypothesis (H₀):** There are no significant differences in average order value across the customer segments identified within the Olist e-commerce platform.
* **Alternate Hypothesis (H₁):** There are significant differences in average order value across the customer segments identified within the Olist e-commerce platform.

The **Null Hypothesis (H₀)** will be rejected if the ANOVA test reveals significant differences in AOV across customer segments, indicated by a p-value less than 0.05 (Bobbitt, 2021). A p-value below 0.05 suggests that the differences are unlikely due to random chance (McLeod, 2023). K-Means clustering will segment customers based on AOV, and ANOVA will compare the means across clusters (Diez et al., 2022). If the null hypothesis is rejected, post-hoc tests like Tukey’s HSD may be applied to identify specific clusters with significant differences (Bobbitt, 2019). This process validates the alternative hypothesis and provides actionable insights for developing targeted marketing strategies.

**Data Collection**

  The data for this project was sourced from a publicly available SQLite database on Kaggle, which contains e-commerce data from Olist, a Brazilian e-commerce platform (Kaggle, 2021). The database comprises multiple tables covering customer transactions, product details, reviews, and other essential attributes (Kaggle, 2021). One key advantage of this data-gathering methodology is that the dataset is preprocessed and curated for public use, ensuring high quality and relevance for the research question (Kaggle, 2021). This eliminates the need for extensive initial cleaning, allowing a focus on analysis. However, a disadvantage is the presence of missing values in critical variables, such as order\_delivered\_customer\_date and review\_score, which could affect the validity of the analysis if not handled appropriately (Kaggle, 2021). To overcome this challenge, records with missing critical data were removed, while non-critical missing values were imputed or handled using dummy variables (edX, 2023). The dataset was queried using SQL to join relevant tables, and Python libraries like Pandas were utilized for further cleaning. The overall data sparsity was determined to be manageable at 4.28%, ensuring sufficient data quality for robust analysis.

Screenshots below to describe how to download a publicly available SQLite database from Kaggle – link [(https://www.kaggle.com/datasets/terencicp/e-commerce-dataset-by-olist-as-an-sqlite-database/data]((https:/www.kaggle.com/datasets/terencicp/e-commerce-dataset-by-olist-as-an-sqlite-database/data)):  
  
A screenshot of a computer

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**A screenshot of a computer

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**Calculation of overall data sparsity:**

**A screen shot of a computer

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**Data Extraction and Preparation**

The data-extraction process started by connecting to an SQLite3 database containing relational tables such as customers, orders, order\_items, products, order\_reviews, and order\_payments. Using SQL queries, I extracted and joined these tables with a combination of JOIN and LEFT JOIN operations to ensure that all relevant information, such as customer details, order information, reviews, and payment data, was combined into a cohesive dataset. The resulting data was loaded into a Pandas DataFrame for further processing.

For data preparation, I used my custom DataFrameProcessor class to automate and standardize the preprocessing steps (Cheung, 2024):

1. **Column Standardization**: All column names were converted to lowercase and spaces were replaced with underscores for consistency (van Rossum et al., 2001).
2. **Handling Missing Values**: Rows with less than 5% missing values were dropped ((Okpara et al., 2022), while categorical variables were imputed with the mode, and numerical variables were imputed using either the mean or median based on skewness (Western Governors University, 2024).
3. **Outlier Handling**: Quantitative outliers were detected using the IQR method, capped within IQR bounds, and visualized using box plots before and after processing (James et al., 2023).
4. **Encoding Categorical Variables**: Binary variables were label-encoded, and non-binary variables were one-hot encoded (Western Governors University, 2024), excluding columns with high cardinality (Aurélien Géron, 2022) or those ending with "id" to avoid excessive dimensionality (Mckinney, 2017).

**Tools Used**:

* **SQLite3**: For efficient database querying and table join (Mckinney, 2017).
* **Pandas**: For flexible data manipulation and preprocessing (Pandas, 2018).
* **Matplotlib**: For visualizing outliers with box plots (Bento, 2020).

**Justification**:

* **Advantage**: This approach provides a repeatable, automated pipeline for preparing clean and analysis-ready datasets. Tools like Pandas simplify preprocessing, while SQL ensures efficient extraction (Speed, 2023).
* **Disadvantage**: SQL queries with multiple joins can be resource-intensive, especially for large datasets, and one-hot encoding may lead to dimensionality issues for high-cardinality variables (Sangani, 2021).

**Screenshots**:

1. SQL query used for extraction and the resulting joined dataset: A screen shot of a computer

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1. Initial dataset structure (.info() output) before preprocessing.



1. <class 'pandas.core.frame.DataFrame'>
2. RangeIndex: 119143 entries, 0 to 119142
3. Data columns (total 20 columns):
4. # Column Non-Null Count Dtype
5. --- ------ -------------- -----
6. 0 customer\_id 119143 non-null object
7. 1 customer\_unique\_id 119143 non-null object
8. 2 customer\_zip\_code\_prefix 119143 non-null int64
9. 3 customer\_city 119143 non-null object
10. 4 customer\_state 119143 non-null object
11. 5 order\_id 119143 non-null object
12. 6 order\_status 119143 non-null object
13. 7 order\_purchase\_timestamp 119143 non-null object
14. 8 order\_delivered\_customer\_date 115722 non-null object
15. 9 order\_approved\_at 118966 non-null object
16. 10 order\_estimated\_delivery\_date 119143 non-null object
17. 11 review\_score 118146 non-null float64
18. 12 review\_comment\_title 13989 non-null object
19. 13 review\_comment\_message 50245 non-null object
20. 14 payment\_type 119140 non-null object
21. 15 payment\_installments 119140 non-null float64
22. 16 payment\_value 119140 non-null float64
23. 17 product\_id 118310 non-null object
24. 18 item\_price 118310 non-null float64
25. 19 freight\_value 118310 non-null float64
26. dtypes: float64(5), int64(1), object(14)
27. memory usage: 18.2+ MB
28. [7]:

3.Visualization of missing values and sparsity in the data:

A computer screen shot of a program

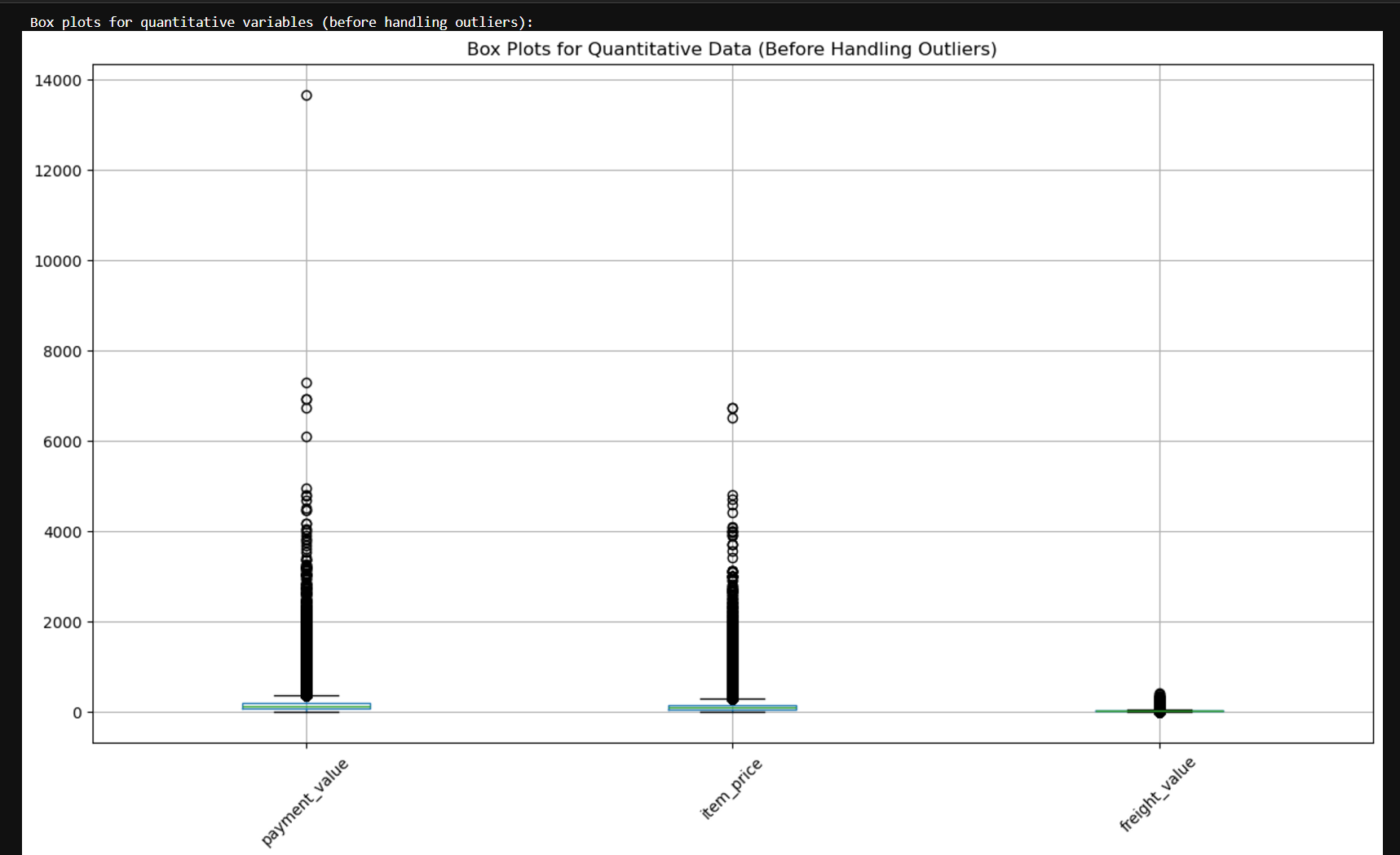
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A screen shot of a computer

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1. Box plots of quantitative variables showing outliers before and after handling:

**Before handling outliers**



**After handling outliers**

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5.Feature Engineering:

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6. Final dataset after scaling (StandardScaler):  
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**Analysis**

To investigate whether significant differences exist in the average order value (AOV) across customer segments within the Olist e-commerce platform, I employed a systematic data-analysis process consisting of **normality testing**, **K-Means clustering**, **statistical testing (ANOVA and Kruskal-Wallis)**, and **visualization techniques**.

**Analysis Techniques:**

**Data Normality Testing**

Data normality testing was conducted to determine if the average order value (AOV) follows a normal distribution, a prerequisite for parametric tests like ANOVA (Mishra et al., 2019). Using Python's scipy.stats.shapiro() function, the Shapiro-Wilk test assessed the normality of AOV (Scipy.stats.shapiro — SciPy V1.3.0 Reference Guide, 2011). The null hypothesis (H₀) assumed normal distribution, but a p-value less than 0.05 indicated that AOV does not follow a normal distribution (Datatab, 2023). If the normality assumption is violated, a non-parametric test alternative, such as the Kruskal-Wallis test, will be needed (Sullivan, 2022).

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**Q-Q Plot:**  
A Q-Q Plot, generated using Matplotlib, provided a visual representation of the data's deviation from normality (Chornyi, 2024).

**Result:** The plot confirmed significant deviations from normality. (Chornyi, 2024).

A graph with a line drawn on it

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**Justification:**  
Normality testing was essential to determine whether parametric or non-parametric tests should be used for statistical analysis (Mishra et al., 2019).

* **Advantage:** Identifies the need for robust alternatives like Kruskal-Wallis when assumptions are violated (Sullivan, 2022).
* **Disadvantage:**

**-** Does not provide actionable insights; it is purely diagnostic (Young, 1993).

**-** Normality tests can yield questionable results when applied to large datasets. These tests may indicate non-normality even when the data visually appears to be normally distributed. Zakaria (2021) emphasizes the importance of complementing statistical tests with graphical methods, such as histograms and Q-Q plots, to make a more accurate assessment of data normality.

**K-Means Clustering**

To segment customers based on their purchasing behavior, **K-Means clustering** was applied (Kashwan & Velu, 2013). This technique grouped customers into clusters with similar behavioral traits, facilitating meaningful comparisons of AOV across segments.

**Steps Performed**:

1. **Feature Standardization**:

Only the **AOV** variable (df\_scaled['aov']) was standardized using Z-scores to ensure the clustering process is not affected by varying scales or extreme values in the data (Firmin, 2023).

1. **Elbow Method**:

* The optimal number of clusters was determined by plotting the inertia (sum of squared distances) against the number of clusters and identifying the "elbow point." (Cui, 2020)
* Result: Four clusters were selected as the optimal number.

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1. **Clustering**:

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K-Means clustering was implemented using Scikit-learn's KMeans module to assign customers into four segments (Babitz, 2018).

The clustering revealed four distinct customer segments, each exhibiting unique purchasing behaviors. Based on the mean AOV of each cluster, I identified high value customers, moderate high value customers, medium value customers, and low value customers.

* **High value customers**: Representing those with the highest AOV.
* **Moderate high value customers**: Customers with above-average AOV but not the highest.
* **Medium value customers**: Customers with average AOV levels.
* **Low value customers**: Customers with the lowest AOV, indicating minimal purchasing behavior.

**Cluster Summary:**

* **Cluster 0**: AOV is around -0.275727 (mean value is scaled, indicating customers with the lowest AOV).
* **Cluster 1**: AOV is around 0.816044 (indicating medium-level customers).
* **Cluster 2**: AOV is around 41.264351 (indicating customers with very high AOV, possibly high-value customers).
* **Cluster 3**: AOV is around 7.474180 (indicating customers with moderately high AOV).

A computer screen shot of a program

Description automatically generated  (Babitz, 2018)

A chart with many dots

Description automatically generated with medium confidence

This scatter plot visualizes clusters based on the Average Order Value (AOV) for customers. The x-axis represents the customer index, while the y-axis shows the AOV. Different colors indicate the clusters (0, 1, 2, and 3), with each cluster representing customers with similar AOV behaviors.

Key observations from the graph include:

1. **Cluster 2 (green)**: This cluster has the highest AOV, represented by the outlier at the top of the graph. It likely corresponds to high-value customers who contribute significantly to revenue.
2. **Cluster 3 (yellow)**: Customers in this cluster show moderately high AOV, scattered throughout the graph, indicating their higher purchasing behavior compared to others.
3. **Cluster 1 (blue)**: This cluster represents customers with low-to-medium AOV. They form the majority of customers and are densely concentrated near the bottom of the plot.
4. **Cluster 0 (purple)**: Customers in this cluster have the lowest AOV, positioned very close to zero, reflecting minimal purchasing behavior.

Statistical Testing

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After clustering, I conducted statistical tests to evaluate the significance of differences in AOV across the identified customer segments.

A one-way **ANOVA** was conducted using Python’s scipy.stats.f\_oneway() function to compare the mean Average Order Value (AOV) across the four customer clusters (F\_oneway — SciPy V1.14.1 Manual, 2014). The null hypothesis, which stated that no significant differences in AOV exist across clusters, was tested against the alternative hypothesis of significant differences (One-Way ANOVA with Python, 2015). The results yielded an **F-statistic of 179080.34 and a p-value of 0.0**, indicating strong statistical significance (One-Way ANOVA with Python, 2015). Consequently, the null hypothesis was rejected, confirming that the clusters exhibit significant differences in AOV, validating the segmentation and highlighting actionable insights for targeted strategies (One-Way ANOVA with Python, 2015).

Since the normality assumption is violated, a non-parametric test alternative, such as the **Kruskal-Wallis test** was performed using Python’s scipy.stats.kruskal() function to assess significant differences in AOV across the four customer clusters (Sullivan, 2022). The null hypothesis, which stated no significant differences in AOV exist across clusters, was tested (Sullivan, 2022). The results yielded a **Kruskal-Wallis statistic of 54555.6175 and a p-value of 0.0**, indicating strong statistical significance (Sullivan, 2022). Consequently, the null hypothesis was rejected, confirming significant differences in AOV across the clusters (Sullivan, 2022). This further validates the effectiveness of customer segmentation.

**Justification for Techniques**

K-Means is an efficient method for segmenting customers into distinct groups, uncovering meaningful behavioral patterns (Kashwan & Velu, 2013). However, it assumes spherical clusters, which may not always align with real-world data distributions (*K-Means Clustering - (Statistical Methods for Data Science) - Vocab, Definition, Explanations | Fiveable*, 2024). ANOVA is a robust technique for comparing means across multiple groups, making it ideal for analyzing AOV differences across clusters (Kenton, 2024). Its limitation lies in its dependence on normality and equal variance assumptions, requiring additional testing or transformations when these are violated (Bobbitt, 2024). The Kruskal-Wallis test offers a non-parametric alternative that does not assume normality, making it well-suited for skewed data (Sullivan, 2022). However, it is less sensitive than ANOVA in detecting subtle mean differences (Bobbitt, 2019). Visualization tools provide an intuitive way to interpret clustering results and statistical findings, enhancing understanding of the data (Clarkson, 2023). While useful, they do not provide statistical precision and should be supplemented with quantitative analyses. (Glenn, 2020).

**Key Insights**

K-Means clustering effectively segmented customers into four distinct groups based on AOV, highlighting clear behavioral patterns. Cluster 2 contained high-value customers with the highest AOV, followed by Cluster 3 (moderate-high AOV), Cluster 1 (medium AOV), and Cluster 0 (low AOV). These insights provide a robust basis for targeted customer strategies.  
Statistical tests, including ANOVA (F-statistic: 179080.34, p-value: 0.0) and the Kruskal-Wallis test (statistic: 54555.6175, p-value: 0.0), confirmed significant differences in AOV across clusters, underscoring the statistical validity of the segmentation.  
 Visualizations, such as scatter plots and bar charts, effectively illustrated the distinct clusters, enhancing the interpretability of both statistical and clustering results (Clarkson, 2023). These visual tools further validated the insights and made them actionable for business applications (Clarkson, 2023).

**Data Summary and Implications**

The analysis revealed significant differences in AOV across customer segments, validated by K-Means clustering, ANOVA, and Kruskal-Wallis tests. High-value customers revealed substantially higher Average Order Value (AOV) compared to other segments, with moderate-high, medium, and low-value groups showing progressively lower AOV. These findings directly address the research question by identifying distinct purchasing behaviors among customer segments and emphasizing the critical role of high-value customers in contributing to Olist's overall earnings.

Limitation of this analysis is the dependence solely on AOV as the metric for customer segmentation. Excluding other behavioral metrics, such as purchase frequency and product categories, may have overlooked additional valuable insights into customer behavior.

To maximize revenue, Olist should prioritize retaining high-value customers through loyalty programs and personalized marketing strategies (Wenzl, 2024). Efforts to engage low-value customers, such as offering discounts or tailored promotions, could enhance their purchasing behavior and increase their overall AOV (Schnelker, 2024).

Future Directions:

1. **Incorporate Additional Features**: Future studies could include variables such as purchase frequency, product categories, or customer demographics to develop a more comprehensive segmentation strategy (Mehta, 2023).
2. **Time-Series Analysis**: Investigate changes in customer behavior over time to identify trends and predict future purchasing patterns for proactive decision-making (Juma, 2023).

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