Introduction
 Payment Type
 Geographical Reach
 Item Categories
 Freight
 Busy Hours
 Conclusion & Next

 Steps



**Olist** connects small businesses to Brazil's top marketplaces without contracts or hassles. Sellers list products on the Olist Store and ship directly with Olist's logistics partners.

#### Objectives:

Explore key e-commerce patterns:

- Payment types
- Geographic reach
- Product categories
- Peak order times

Build a regression model to predict freight costs based on order weight.

#### Data Limitations

- Missing geolocation data led to approximation using nearest valid location
- 676 delivered orders had no review scores
- Up to 830 records had missing values likely from incomplete or failed orders

#### Dataset includes:

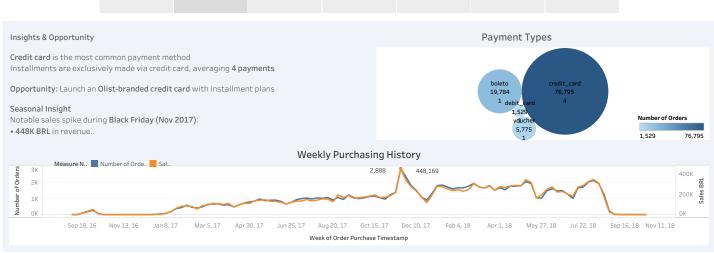
Brazilian e-commerce order data from Olist Store, with 100K+ orders from 2016-2018 across multiple marketplaces

## It covers:

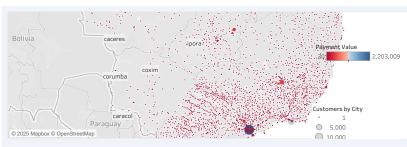
- Order status, price, payment, and freight details
- Customer locations and product attributes
- Customer reviews and satisfaction
- Geolocation data linking ZIP codes to lat/Ing coordinates







Introduction Payment Type Geographical Reach Item Categories Freight Busy Hours Conclusion & Next Steps



#### Interactive Map Insight

The map above shows **customer cities**, highlighting **revenue** and **order size** across Brazil.

#### Strategic Recommendations

- Enlist sellers in underserved inland and northern regions
- Add a distribution center to manage high-demand inventory in those areas
- Inform sellers about local warehouse needs based on order volume..









#### Customer Distribution

São Paulo leads with 43K customers, followed by Minas Gerais with 14K. Other states have up to 7K, reflecting Brazil's population distribution.

#### Seller Locations

Most sellers are concentrated in São Paulo (73K). Several states show **little to no seller presence**, especially those in dark blue.

#### Revenue by State

Total sales value is highest in São Paulo (~5M BRL) and Minas Gerais (>3M BRL), indicating strong customer bases and purchasing activity.

#### Average Spend per Customer

When normalized by customer count, smaller states show higher average spend. This may suggest demand for high-ticket items not readily available locally...

Introduction Payment Type Geographical Reach Item Categories Freight Busy Hours Conclusion & Next
Steps

	Which category items	sell more? What	is their review	score?			Category Performance Treemap
health_beauty 1,439,926 4.177	sports_leisure 1,157,754 4.174	housewares 780,774 4.149	toys 560,986 4.196	baby 479,640 4.059	perfumery 454,238 4.181	telephony 395,290 4.009	The treemap displays revenue by product category alongside average customer review scores.  Key Insight  • Top-revenue categories generally receive high review
watches_gifts 1,303,160 4.068	computers_accessories 1,057,630 4.034	cool_stuff 720,652 4.176		electronics 208.256		#N/A	scores  • However, some categories—like Office Furniture (avg. score: 3.65)—underperform in customer satisfaction  Strategic Use
bed_bath_table	furniture_decor	auto 685,302 4.096	stationery 278,325 4.253 pet_shop	unknown 207,408			Useful for identifying top categories when selecting sellers or planning distribution centers     This insight can also help sellers improve service quality
1,240,930 3.977	906,602 4.031	garden_tools 584,380 4.122	254,439 computers 231,394				Further analysis is recommended to explore causes of low review scores in specific categories  Payment V. 325  1,439,926

Introduction	Payment Type	Geographical Reach	Item Categories	Freight	Busy Hours	Conclusion & Next
						Steps

## Freight Cost vs. Product Weight

#### Key Findings

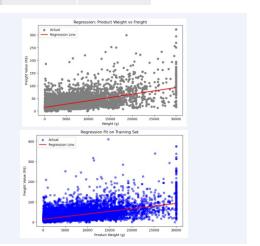
- $\bullet$  A  $\it linear \, regression \, model$  was built to predict freight cost based on product weight
- Slope: R\$0.0026 per gram
- RMSE: ~R\$12.50 average prediction error
- $R^2$  Score: ~0.38 38% of variation in freight cost is explained by weight

## Model Performance

- Test RMSE: R\$12.69 (slightly higher, shows minor generalization error)
- R<sup>2</sup> Consistency: 0.38 (train) vs. 0.39 (test) indicates good generalization
- Conclusion: Weight impacts freight, but other factors (e.g., size, distance, carrier) matter too



Metric	Training Set	Test Set
Slope	0.0026	0.0026
RMSE (R\$)	12.50	12.69
R <sup>2</sup> Score	0.382	0.385

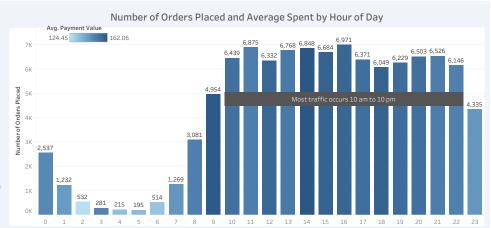


Introduction Payment Type Geographical Reach Item Categories Freight Busy Hours Conclusion & Next Steps



#### Order Timing & Revenue Insight

- Most orders are placed between 10 AM and 10 PM, indicating a strong marketing opportunity window for sellers during this time.
- The bar chart also shows average revenue per order by hour, ranging from 124 to 162 BRL—a narrow gap, suggesting purchase amount is consistent throughout the day.
- Slight peaks at 9 AM and 2 PM show the highest average order values, which could be leveraged for targeted promotions.



Introduction Payment Type Geographical Reach Item Categories Freight Busy Hours Conclusion & Next Steps



## Conclusion

Insights from Olist's data reveal key trends in customer behavior, product performance, and regional demand.

A regression model showed a moderate relationship between freight cost and product weight, suggesting room for improvement by incorporating additional features like volume and shipping location.

#### Opportunities include:

- Launching an Olist credit card
- Expanding seller presence in underserved regions
- Improving freight prediction with more features

Altogether, these findings provide a strong foundation for data-driven decisions to improve customer satisfaction, seller performance, and overall operational efficiency.



#### **Next Steps**

# Enhance Freight Model

Include product dimensions, shipping distance, and delivery method to improve prediction

#### Seller Strategy

 $Identify\ high-potential\ regions\ with\ low\ seller\ presence\ and\ recommend\ seller\ onboarding\ or\ distribution\ hubs.$ 

# Customer Segmentation

Cluster customers by behavior (e.g., spend, location, review score) to tailor marketing and service.

#### Category Deep-Dive

 $\label{thm:local-performing} Analyze\ low-performing\ categories\ (e.g.,\ Office\ Furniture)\ to\ uncover\ drivers\ of\ poor\ reviews.$ 

Credit Strategy..