

# On Time or Not?

Predicting Delivery Delays on Brazil's largest e-commerce platform, Olist

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October 24, 2025

# 1 Problem Introduction

Have you ever ordered something online, checked the tracking page five times a day, and still wondered — “*Why hasn’t my package arrived yet ???*”



## Problem Definition:

Predict whether an e-commerce order will be delivered on time.

## Why It Matters:

- **Delivery punctuality → key to customer satisfaction**
- **Late orders → harm seller reputation**
- **Accurate delay prediction → optimize logistics operations**

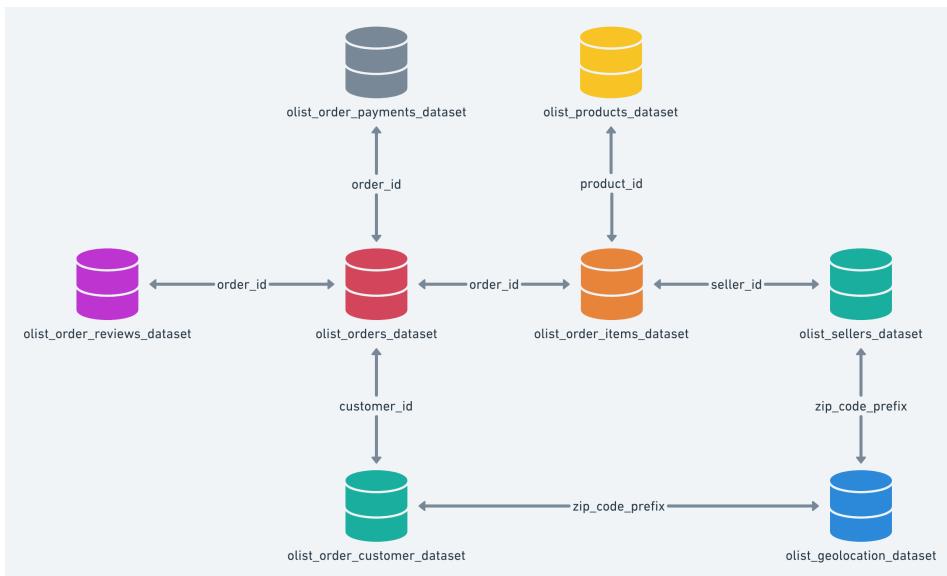
## Type of Task: Binary Classification

- **Target: `is_late` (actual delivery date VS the estimated delivery date)**
- **1 → Delivered after estimated date**
- **0 → Delivered on time**



## 2 Dataset

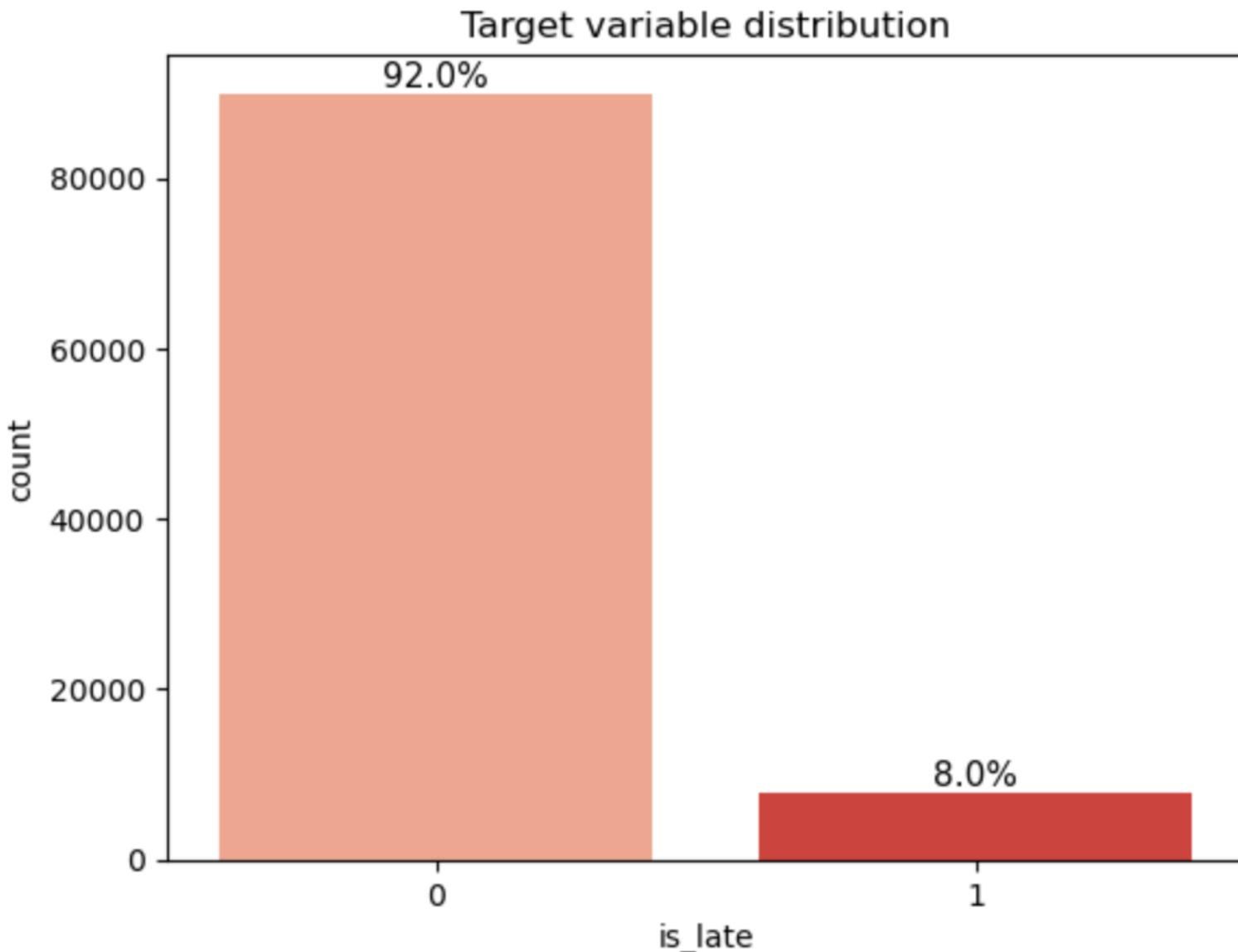
- Source: Olist — Brazil's largest e-commerce platform
- Public release on Kaggle (Olist data-sharing initiative)
- Real transactional records from 2016–2018
- Each row = one real order



## Three challenges:

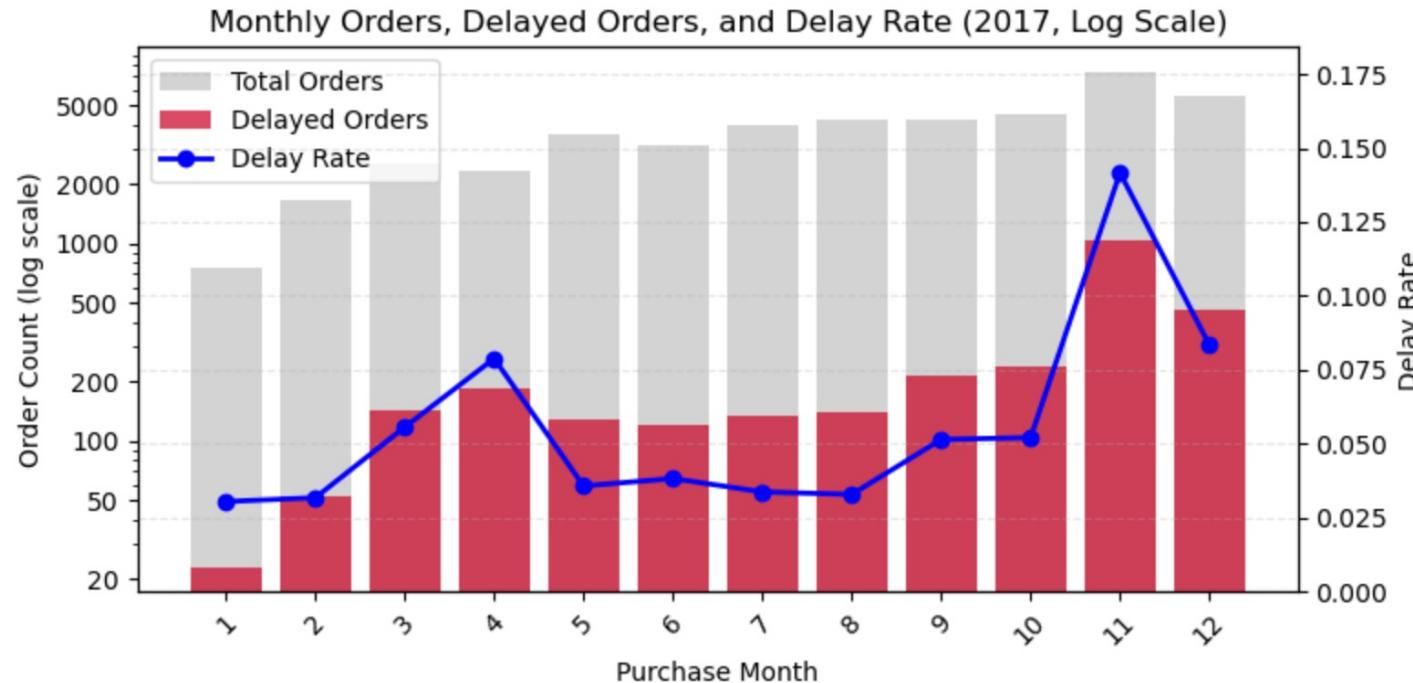
- Large: over 100k orders and multiple linked tables.
- Non-iid : multiple orders come from the same customers  
(each order is an independent sample in my task)
- Some tables contain missing values(<0.1% ) .

### 3 EDA

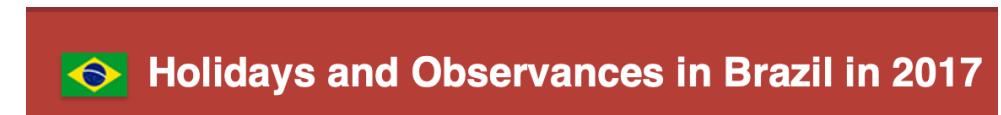


**A strong class imbalance**

# 3 EDA

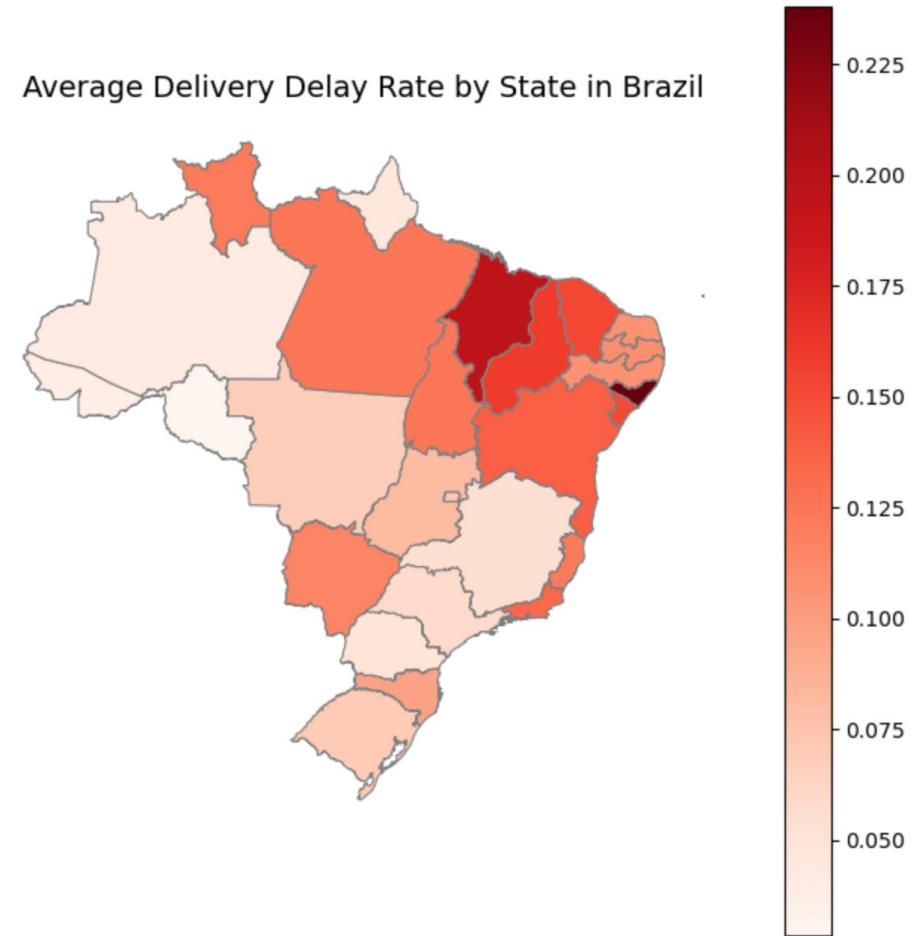
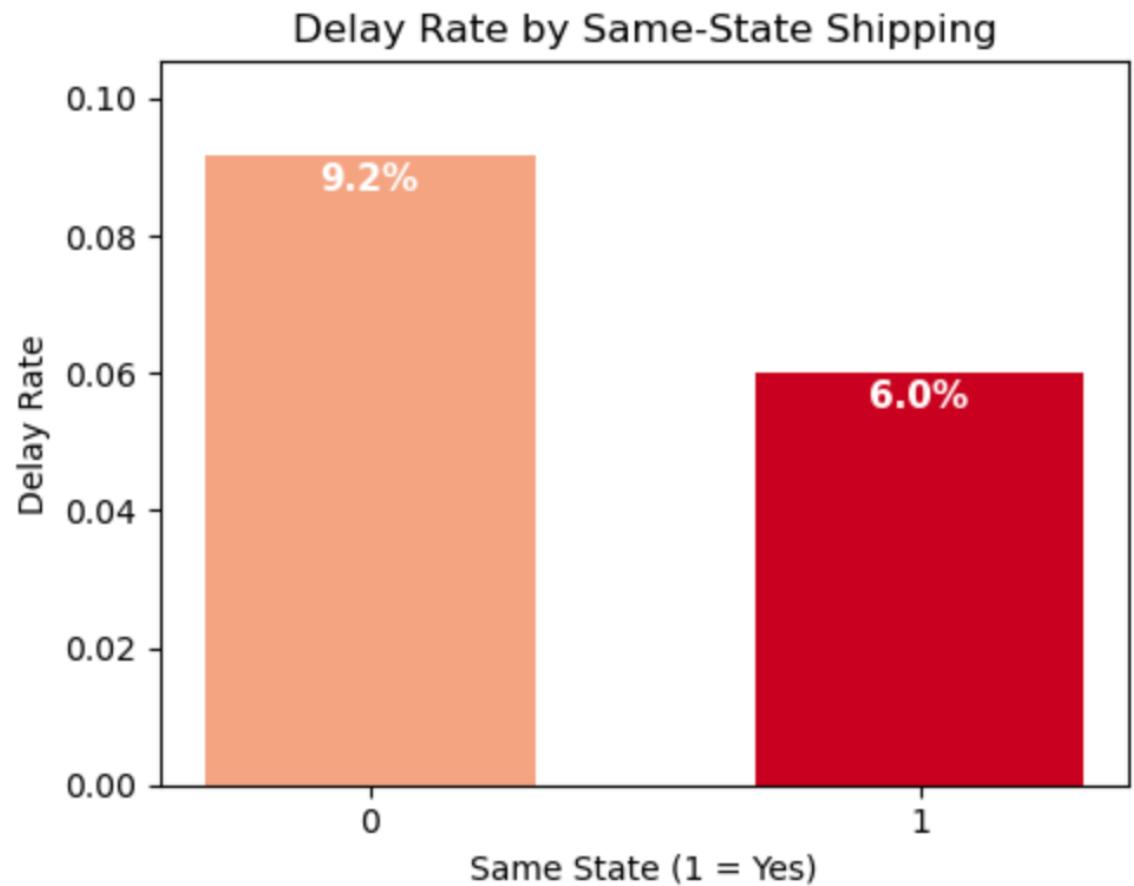


- Delay peaks in November (Black Friday)
- Second spike in April (National public holidays)
- Holiday/Shopping Period cause?



Apr 14	Friday	Good Friday	National Holiday
Apr 16	Sunday	Easter Sunday	Observance
Apr 21	Friday	Tiradentes Day	National Holiday
May 1	Monday	Labor Day	National Holiday

### 3 EDA



- Cross-state orders → higher delay rate
- Same-state orders → fewer delays
- Shipping distance likely main factor

# 4 Splitting and Preprocessing

## Splitting:

- Used a stratified train-test split to divide the dataset into 80% training + validation and 20% test.
- Within the 80% training + validation portion, applied 4-fold StratifiedKFold cross-validation

Train+Val size: (78255, 15), Test size: (19564, 15)

Fold 1

Train shape: (58691, 68), Val shape: (19564, 68), Test shape: (19564, 68)

Fold 2

Train shape: (58691, 68), Val shape: (19564, 68), Test shape: (19564, 68)

Fold 3

Train shape: (58691, 68), Val shape: (19564, 68), Test shape: (19564, 68)

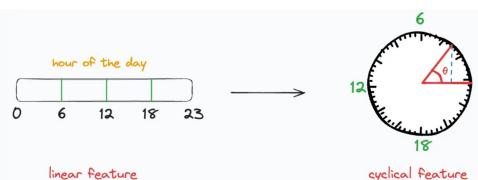
Fold 4

Train shape: (58692, 67), Val shape: (19563, 67), Test shape: (19564, 67)

Feature Group	Features & Descriptions
Numeric (7)	<ul style="list-style-type: none"><li>n_items - number of items per order</li><li>total_price - total product value</li><li>total_freight - total shipping cost</li><li>avg_price - average price per item</li><li>payment_value - actual payment amount</li><li>seller_avg_score - seller's average review score</li><li>purchase_to_estimated_days - promised delivery duration</li></ul>
Ordinal (1)	<ul style="list-style-type: none"><li>payment_installments - number of payment installments</li></ul>
Categorical (4)	<ul style="list-style-type: none"><li>main_payment_type - payment method</li><li>same_state - 1 if buyer &amp; seller are in same state</li><li>customer_state - customer's state code</li><li>seller_state - seller's state code</li></ul>
Cyclic (2)	<ul style="list-style-type: none"><li>purchase_month - month of purchase (1-12)</li><li>purchase_dow - day of week (0-6)</li></ul>

## Preprocessing:

- StandardScaler → numerical & linear ordinal features
- OneHotEncoder → categorical features (payment\_type, state)
- Cyclic encoding → temporal features (month, day\_of\_week)



Picture from blog [cyclical-feature-engineering](#)

# Q&A