SC1015 Mini-Project: Predicting E-Commerce Order Cancellations

FR1 | Group 8
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Project Motivation

Order cancellations cause lost revenue, wasted logistics, and inventory issues

Even a small % of cancellations can lead to major operational inefficiencies

Customer trust and satisfaction are negatively impacted by cancellations

Identifying high-risk orders early can lead to cost savings and better planning

A data-driven approach can help predict and reduce cancellations at scale

Problem

Can we use order-level data to predict order cancellations and reduce revenue loss?

Dataset Overview

Source and Scope

- Real-world dataset from Amazon.in, downloaded from Kaggle
- Contains around 128,975 e-commerce transactions
- Includes product, fulfillment, pricing, and order status details

Variables Selected

Fulfilment method (Amazon vs Merchant)

Ship service level (Standard vs Expedited)

Amount paid by the customer

Promotion type (e.g., No Promo, Free Shipping, PLCC, etc.)

Product category

Target Variable

Order Status

Data Cleaning & Preparation

Removed irrelevant identifiers

Variables to keep

Status
Fulfilment
ship-service-level
Category
Amount
promotion-ids

Variables to add

Category_name

to ensure interpretability of the analysis

Variables to remove

Order ID
Date
Sales Channel
Style
SKU
Size
ASIN
Courier Status
Qty
currency
ship-city
ship-state
ship-postal-code
ship-country
B2B
fulfilled-by
index
Unnamed: 22

Handle Missing Values

- Filled missing values in promotion-ids with "no"
- Filled missing values in Amount with 0

Target Filtering

Filtered dataset to only include Cancelled and Completed orders

Feature Encoding

- Converted Fulfilment, Shipping level, and Promotion type to numeric format
- Encoded Order Status as binary: 1 = Cancelled, 0 = Completed

convert categorical variables into numerical format so that machine learning models can process them

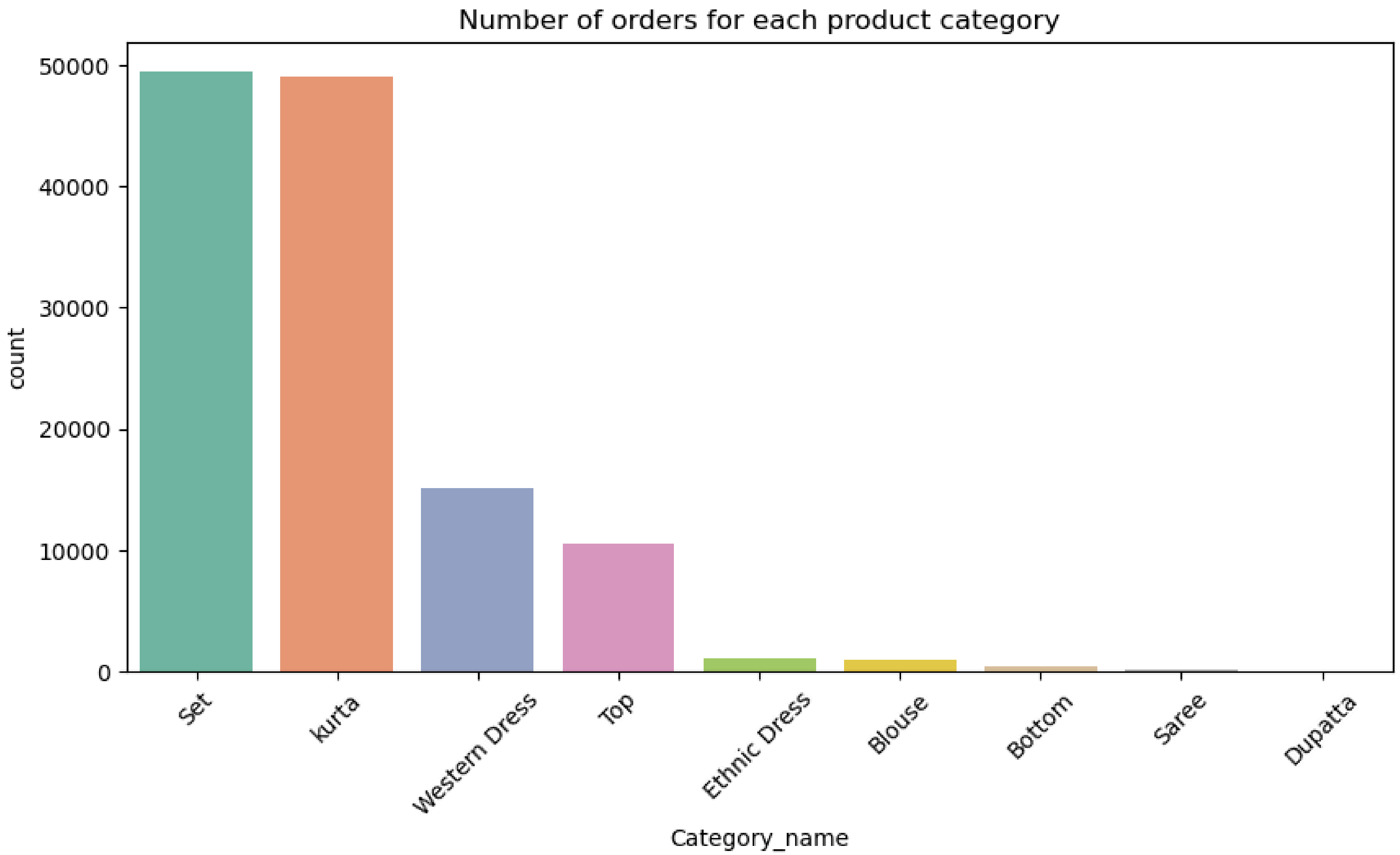
Cleaned Dataframe

```
df
```

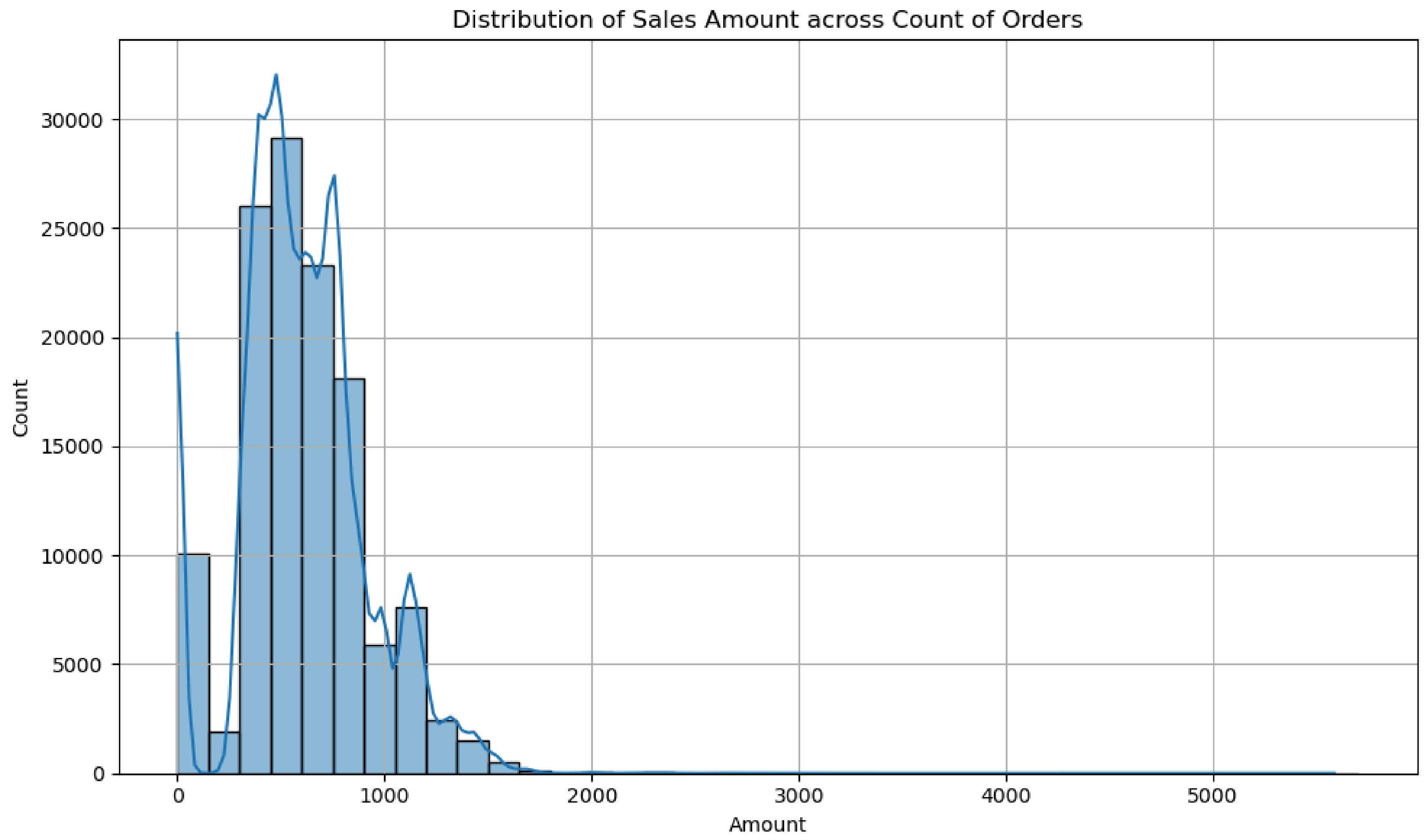
	Status	Fulfilment	ship-service-level	Category	Amount	promotion-ids	Category_name
0	1	1	0	5	647.62	0	Set
1	0	1	0	8	406.00	2	kurta
2	0	0	1	8	329.00	1	kurta
3	1	1	0	7	753.33	0	Western Dress
4	0	0	1	6	574.00	0	Top
...	...	...	...	...	...	...	...
128970	0	0	1	8	517.00	0	kurta
128971	0	0	1	5	999.00	1	Set
128972	0	0	1	7	690.00	0	Western Dress
128973	0	0	1	5	1199.00	1	Set
128974	0	0	1	5	696.00	1	Set

126825 rows × 7 columns

Exploratory Data Analysis

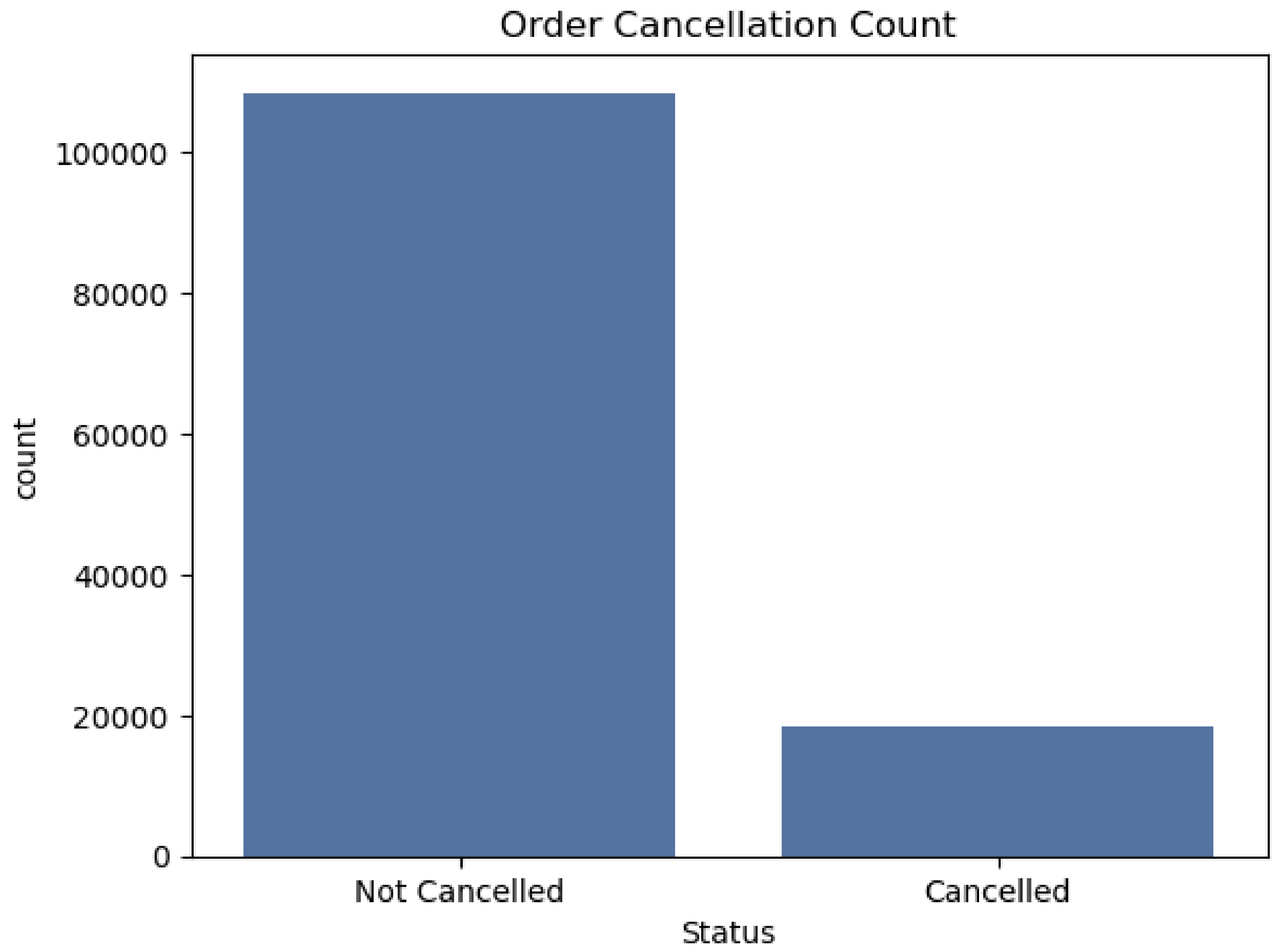


- The majority of orders come from just a few product categories, indicating a highly imbalanced category distribution.
- To ensure model stability and avoid noise from low-frequency categories, we decided to focus on the top 4 product categories for modeling.

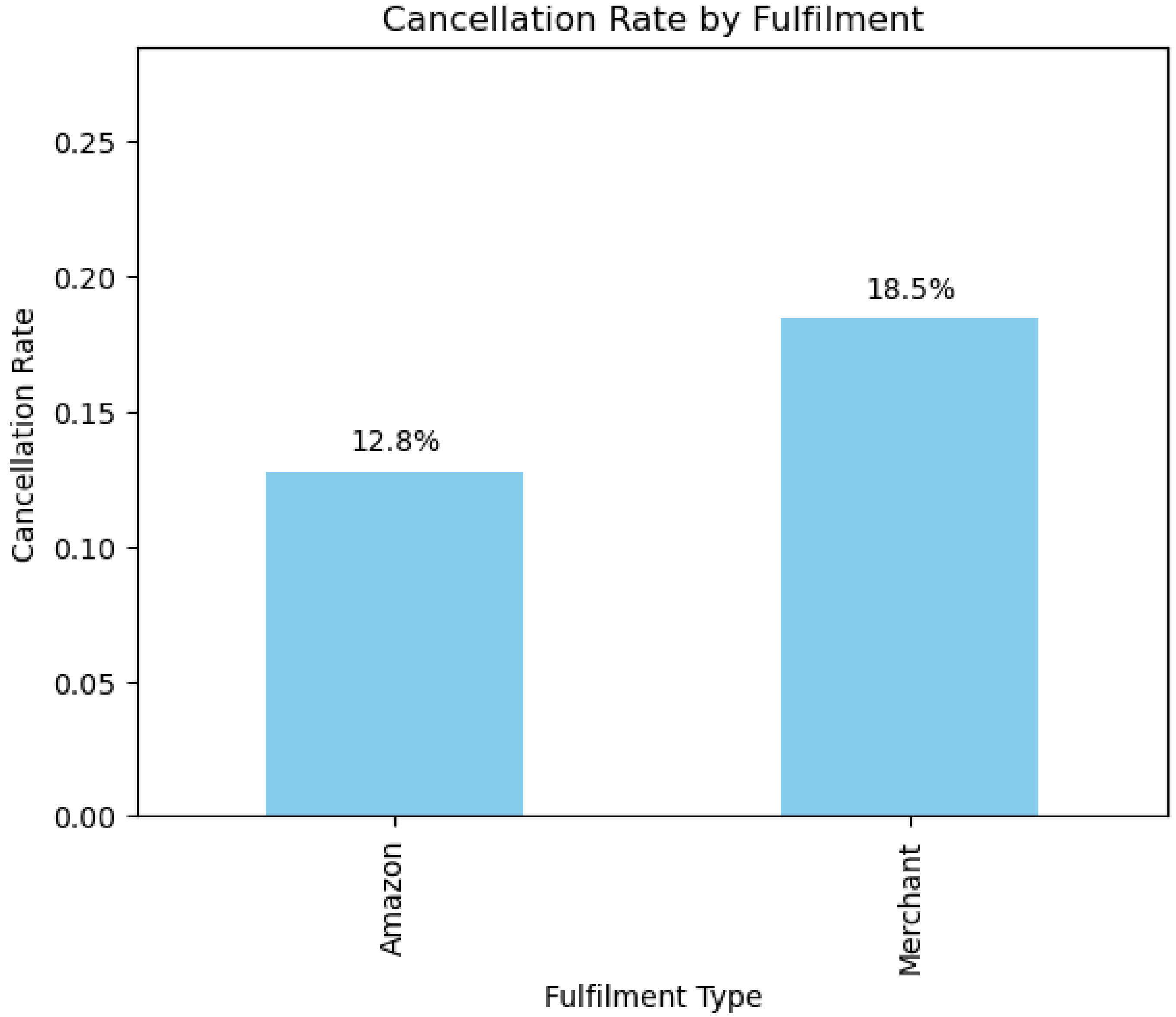


- Most orders are between ₹300–₹1000.
- The distribution is right-skewed with a long tail of high-value orders.

Exploratory Data Analysis

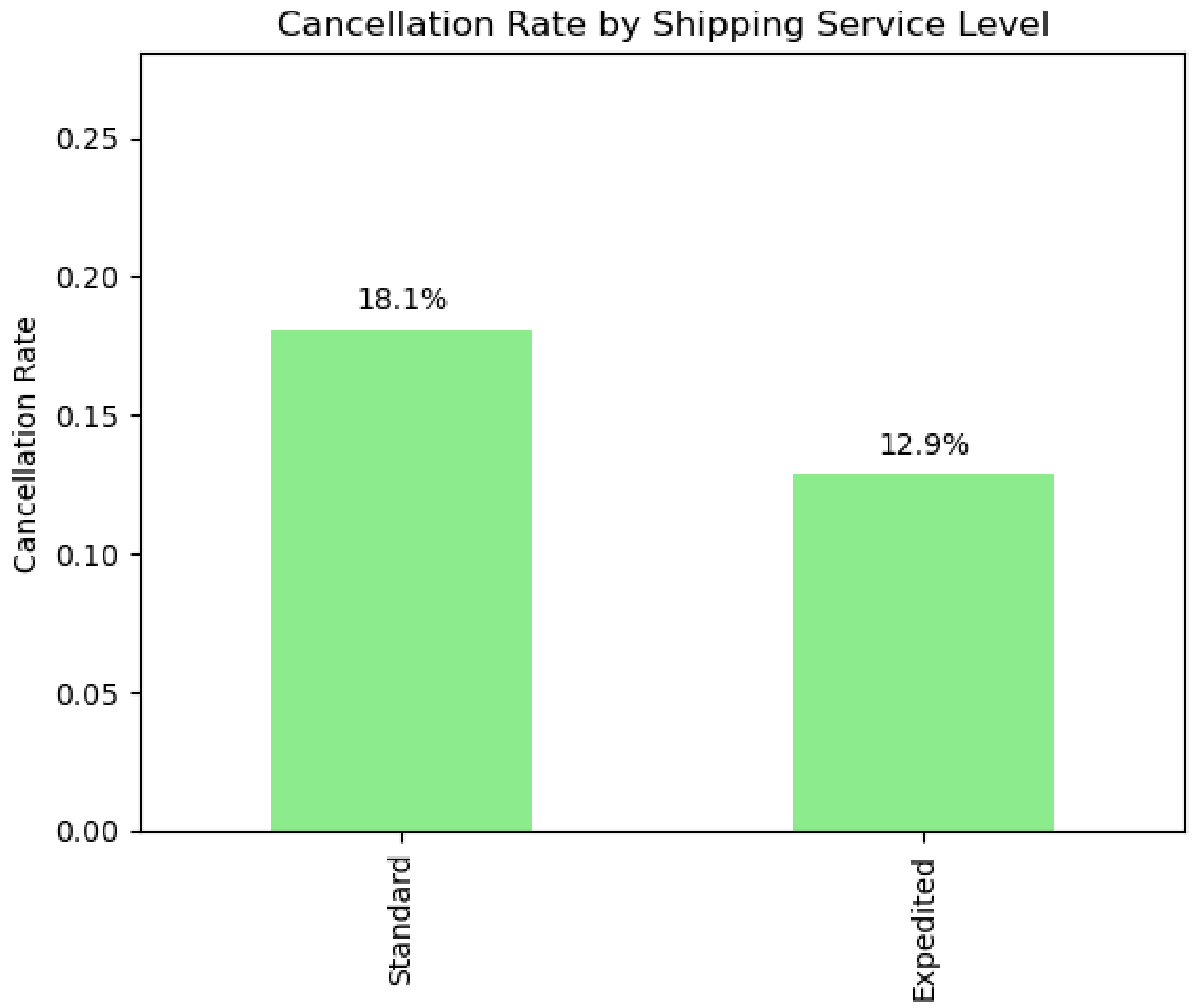


- 85.55% of orders are Not Cancelled
- 14.45% of orders are Cancelled
- Significant class imbalance – needs to be addressed in modeling (e.g., using class weights)

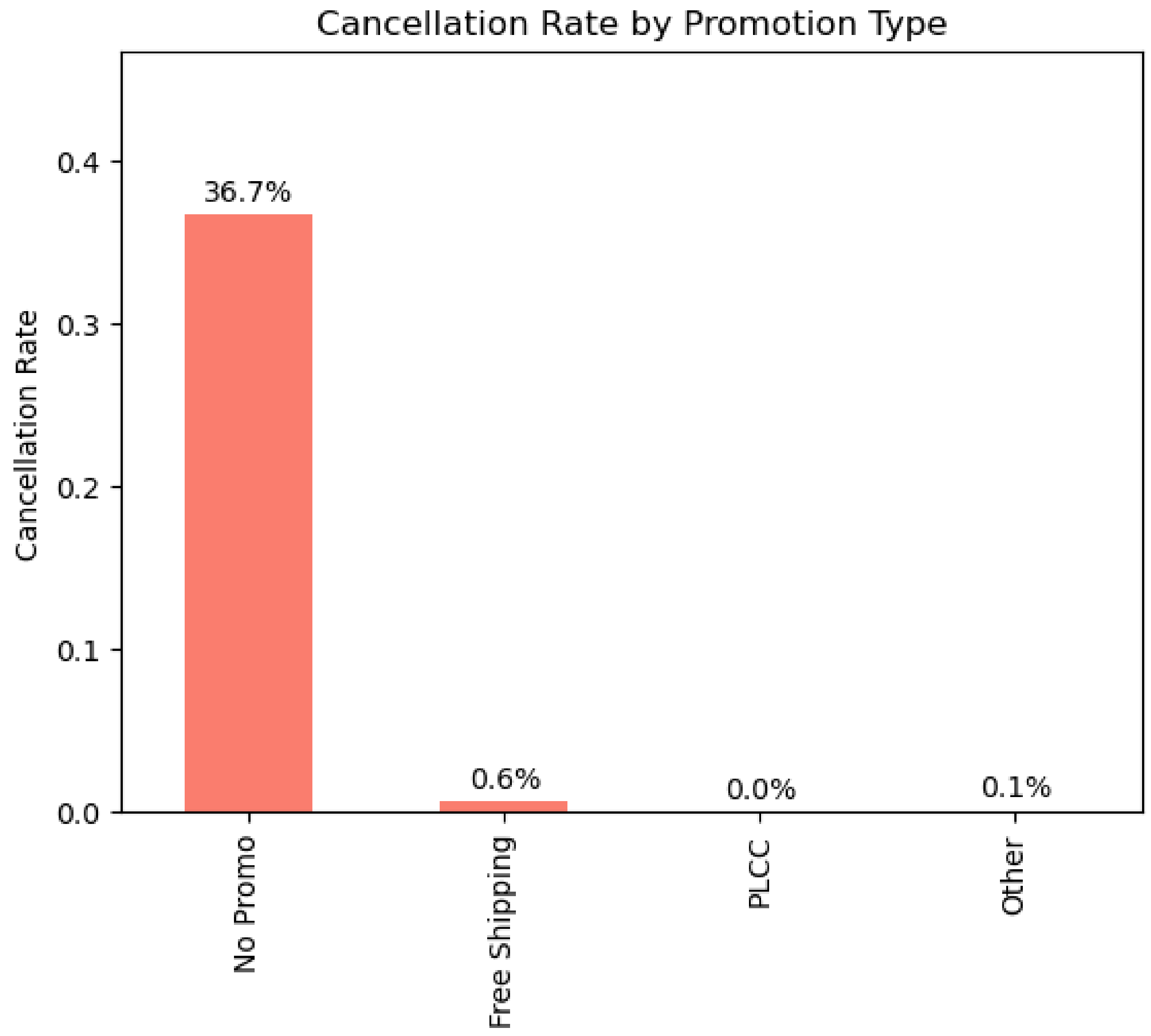


- Merchant orders are ~45% more likely to be cancelled
- Fulfilment method is a key factor influencing cancellations

Exploratory Data Analysis

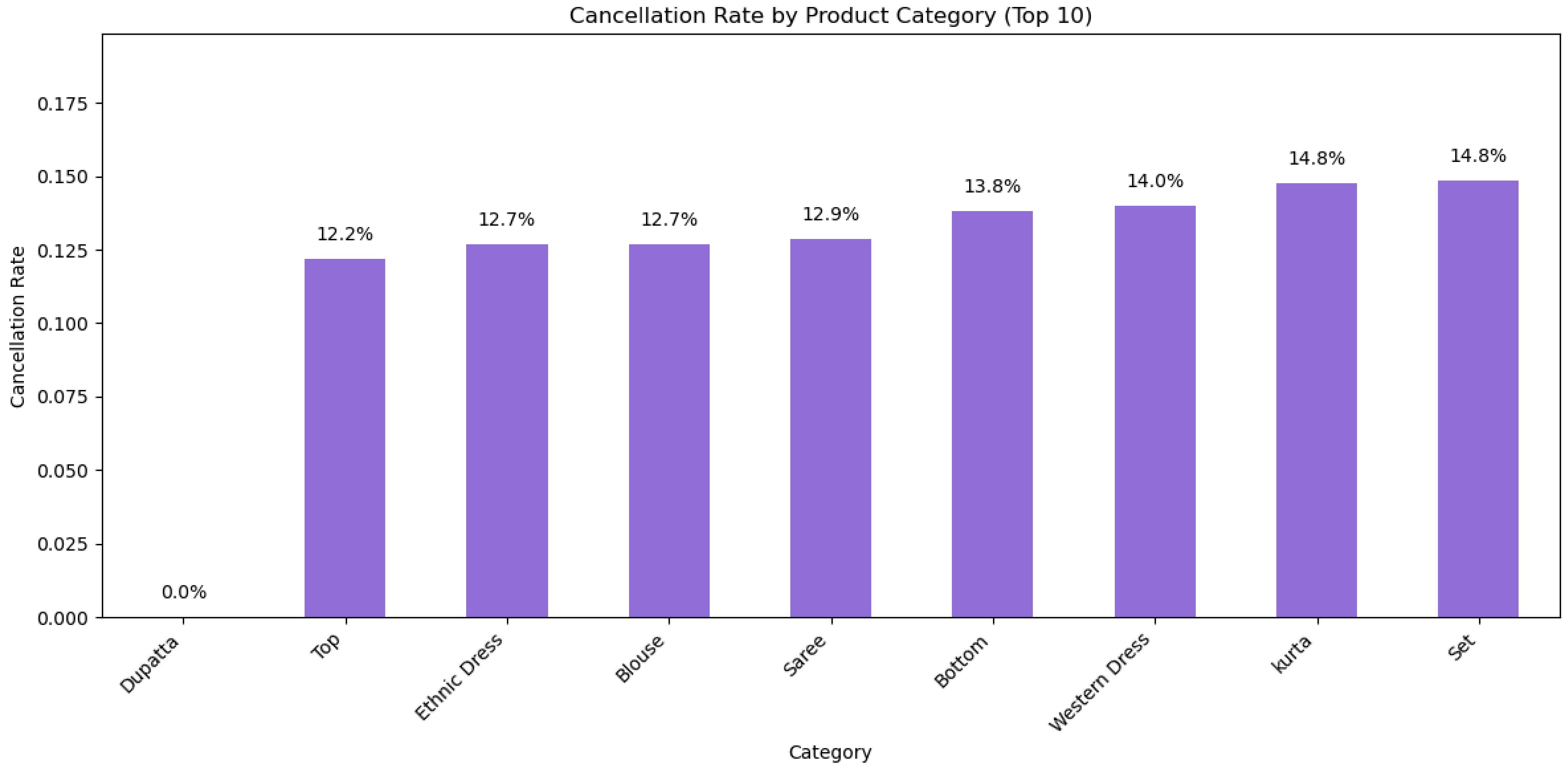


- Faster delivery is associated with lower cancellation likelihood
- Shipping speed is a relevant feature for cancellation prediction



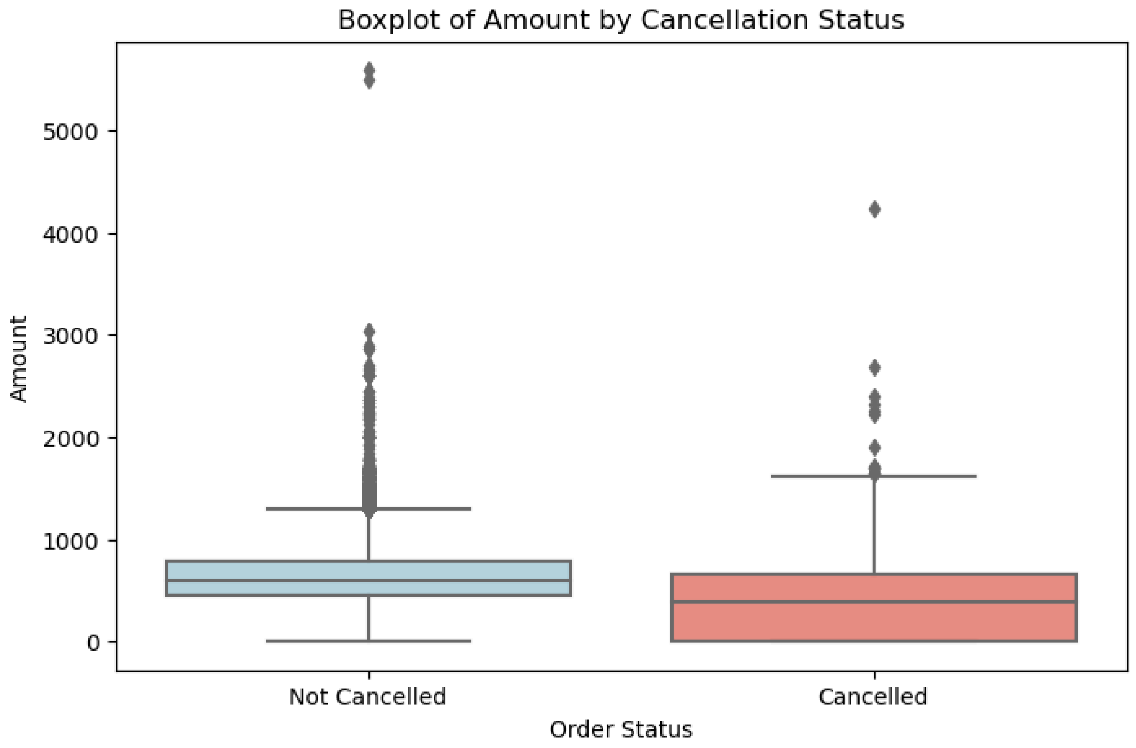
- Promotions significantly reduce the risk of order cancellation
- Promotion Type is a highly predictive feature

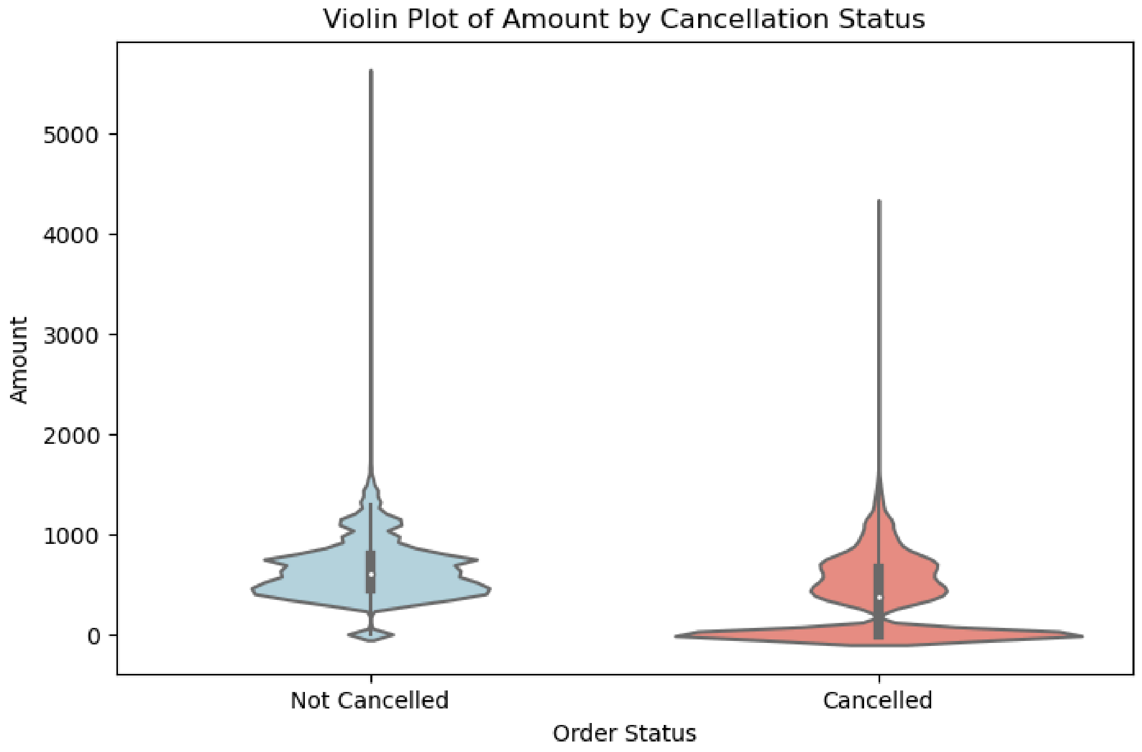
Exploratory Data Analysis

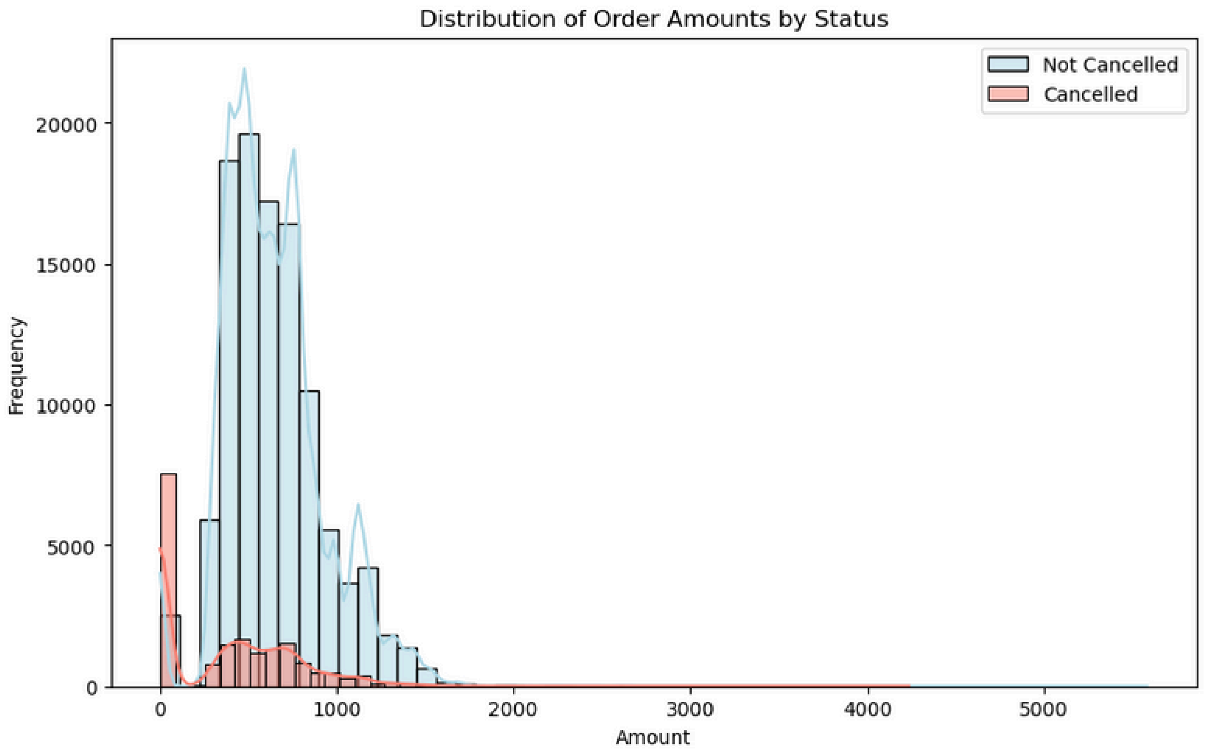


- Highest cancellation in Set and Kurta (14.8%) — also top-selling categories
- Suggests product type may influence cancellation behavior

Exploratory Data Analysis

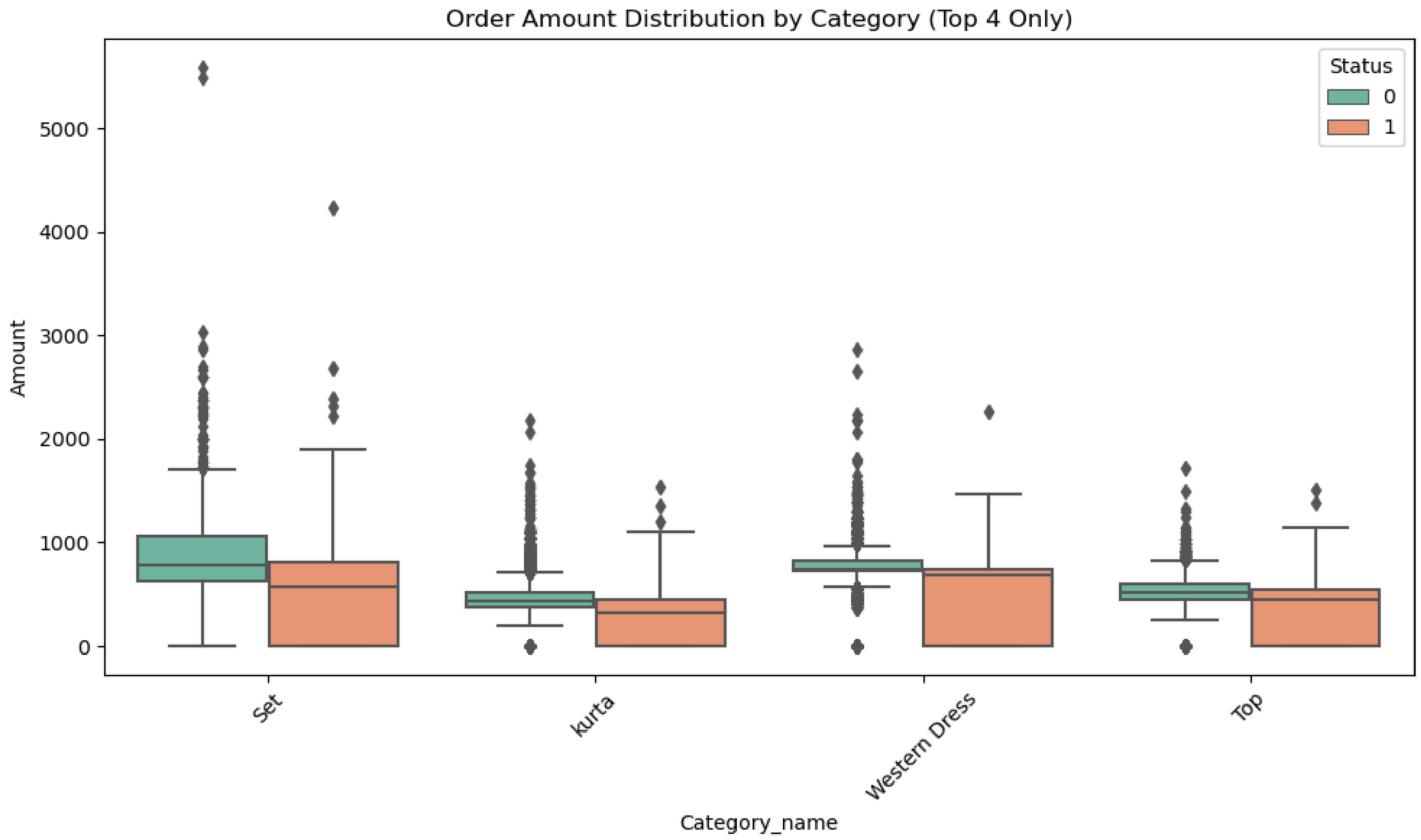






- Cancelled orders are typically lower in value.
- Higher-value orders are less likely to be cancelled.
- While order amount alone may not fully explain cancellations, it helps enhance predictions when used alongside fulfilment type, promotion, and category.

Exploratory Data Analysis



- In the top 4 categories, cancelled orders tend to be lower in value
- Suggests order amount + category interaction may be predictive
- These patterns are important for modeling cancellation risk

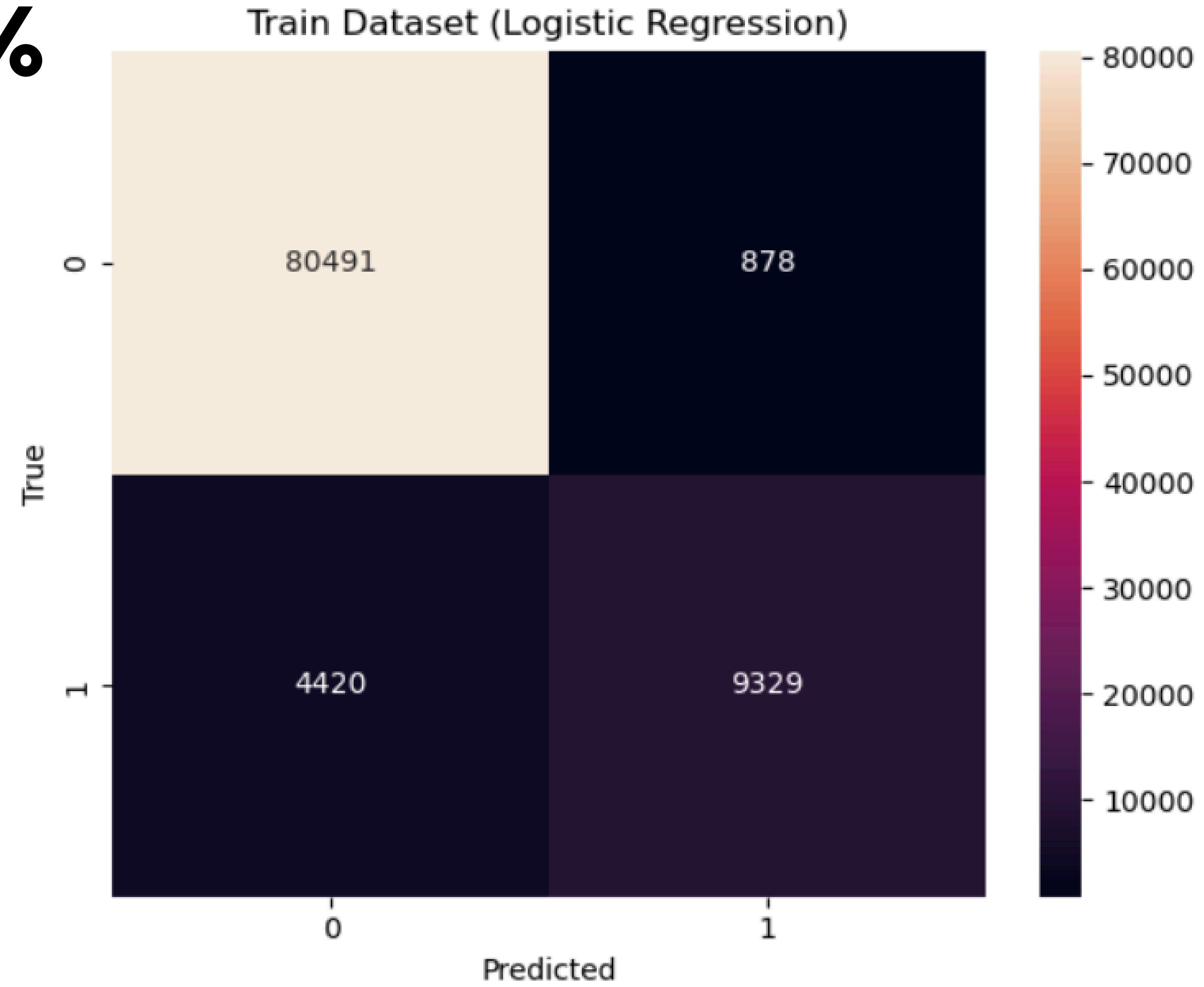
Machine Learning

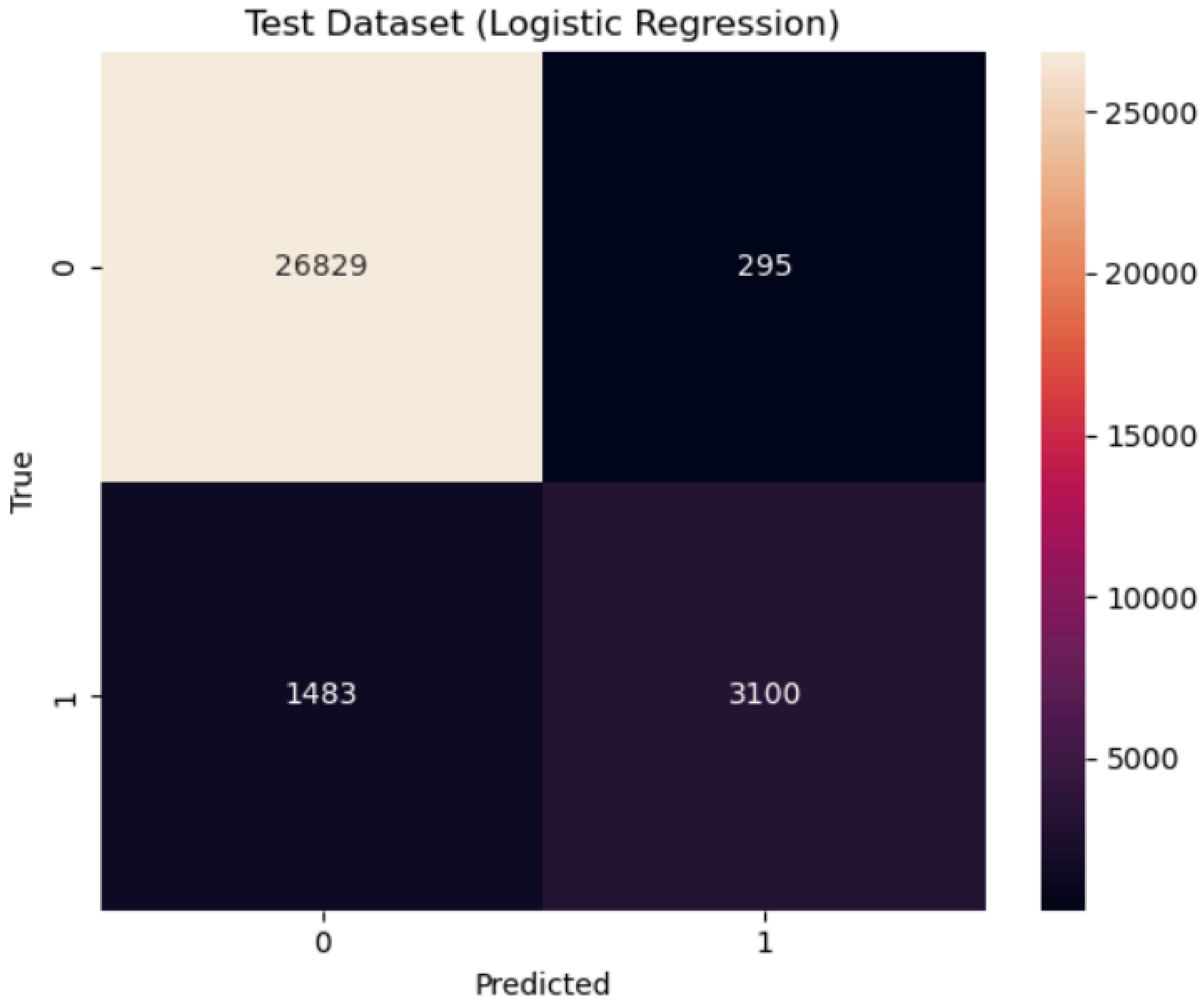
- *Logistic Regression*
- *Random Forest*
- *eXtreme Gradient Boosting*

Logistic Regression

- Used as a **baseline model** to test if order features are predictive of cancellations
- Simple and interpretable: easy to understand the relationship between features and target
- Fast and efficient to train, especially on large datasets or early-stage analysis

75%

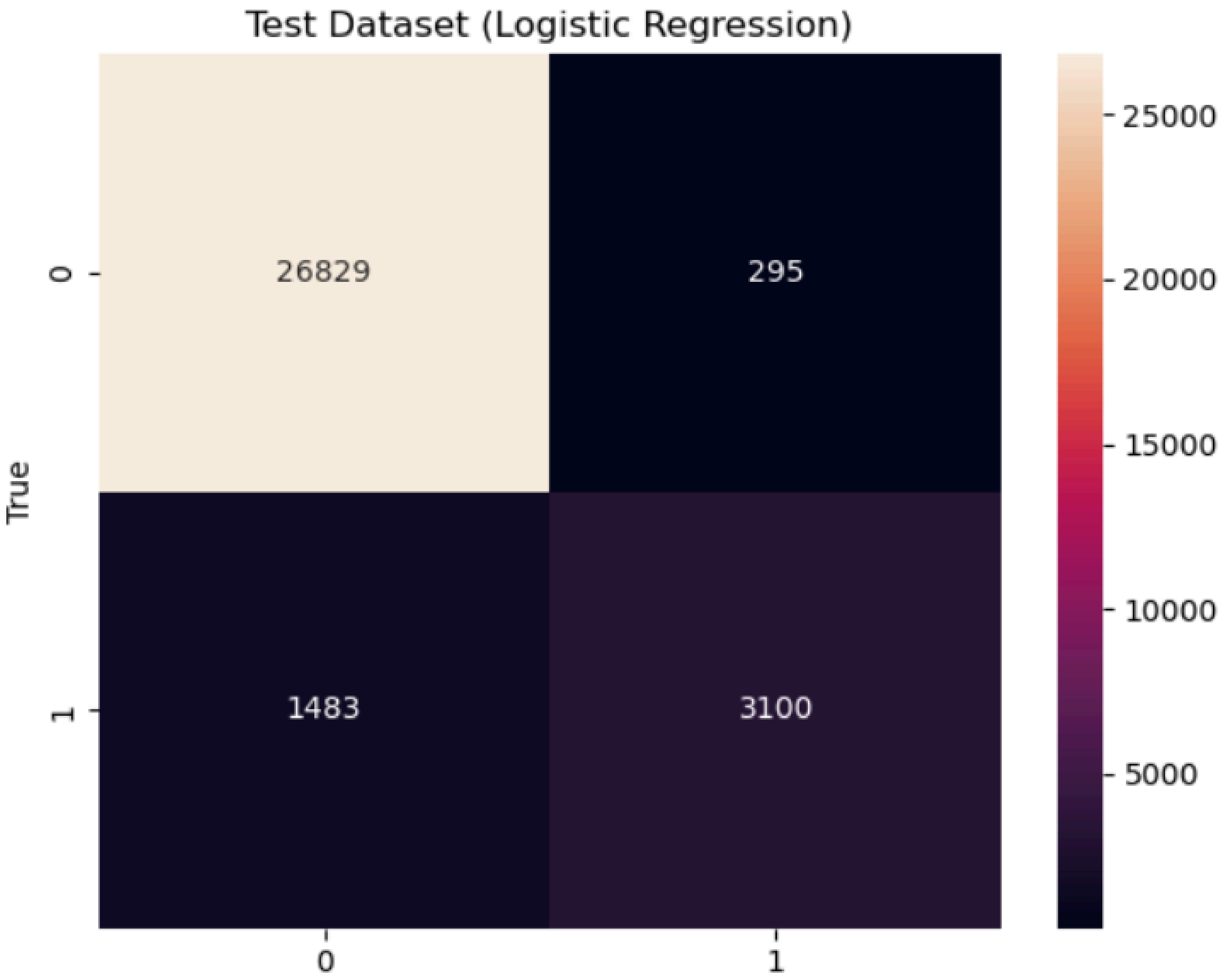




25%

Logistic Regression

```
Goodness of Fit of Model: Test Dataset
Classification Accuracy :  0.9439
True Negative Rate      :  0.9891
True Positive Rate      :  0.6764
False Negative Rate     :  0.3236
False Positive Rate     :  0.0109
```



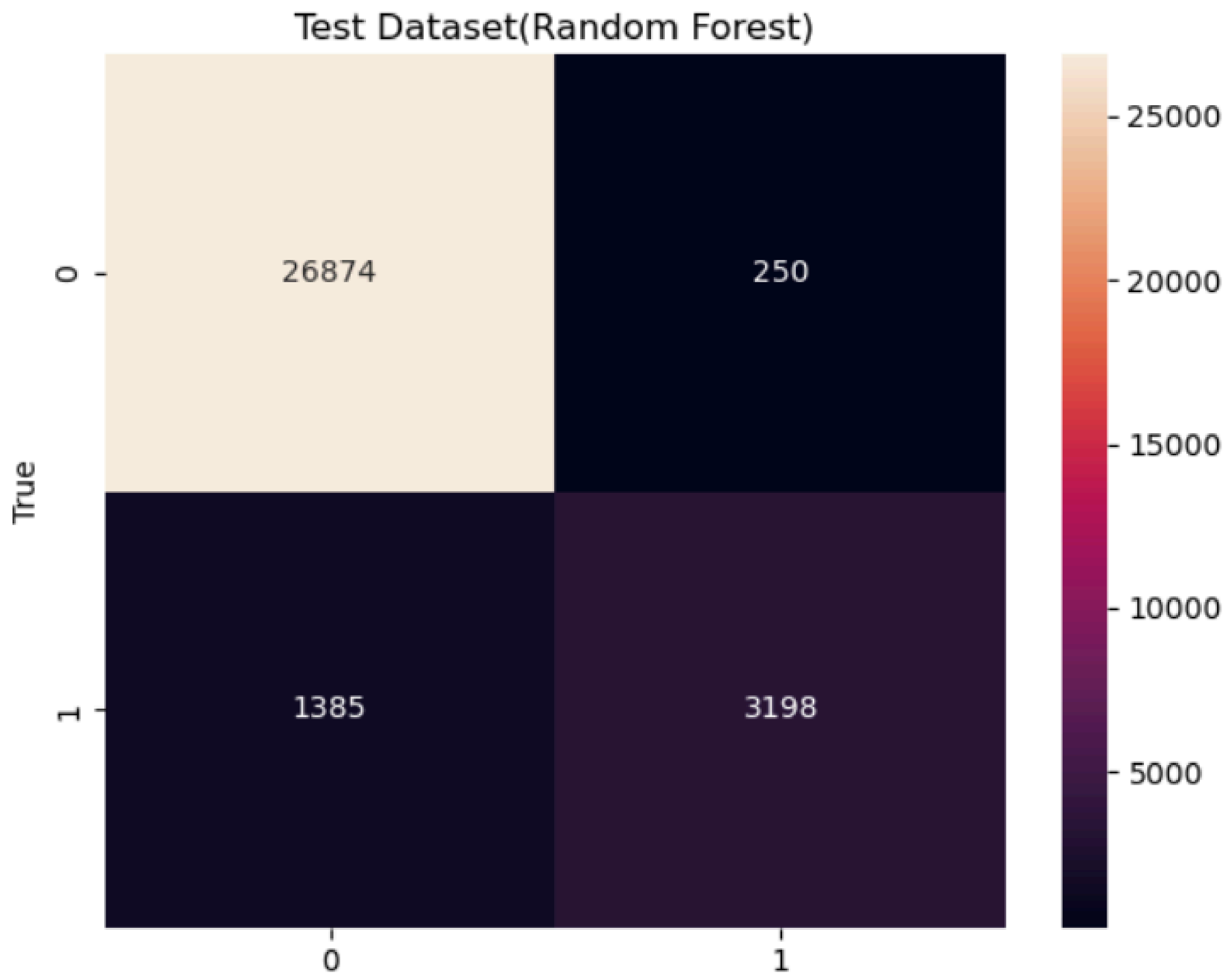
Accuracy: 94.39%
→ Overall prediction is highly accurate; the model performs well on general order classification.

True Negative Rate: 98.91%
→ Excellent at identifying non-cancelled orders; very few "good orders" are mistakenly flagged.

True Positive Rate (Recall): 67.64%
→ Correctly catches about two-thirds of cancelled orders, but misses ~32% of high-risk cases.

Random Forest

```
Goodness of Fit of Model: Test Dataset(Random Forest)
Classification Accuracy :  0.9484
True Negative Rate      :  0.9908
True Positive Rate      :  0.6978
False Negative Rate     :  0.3022
False Positive Rate     :  0.0092
```



Why Are the Results Similar?

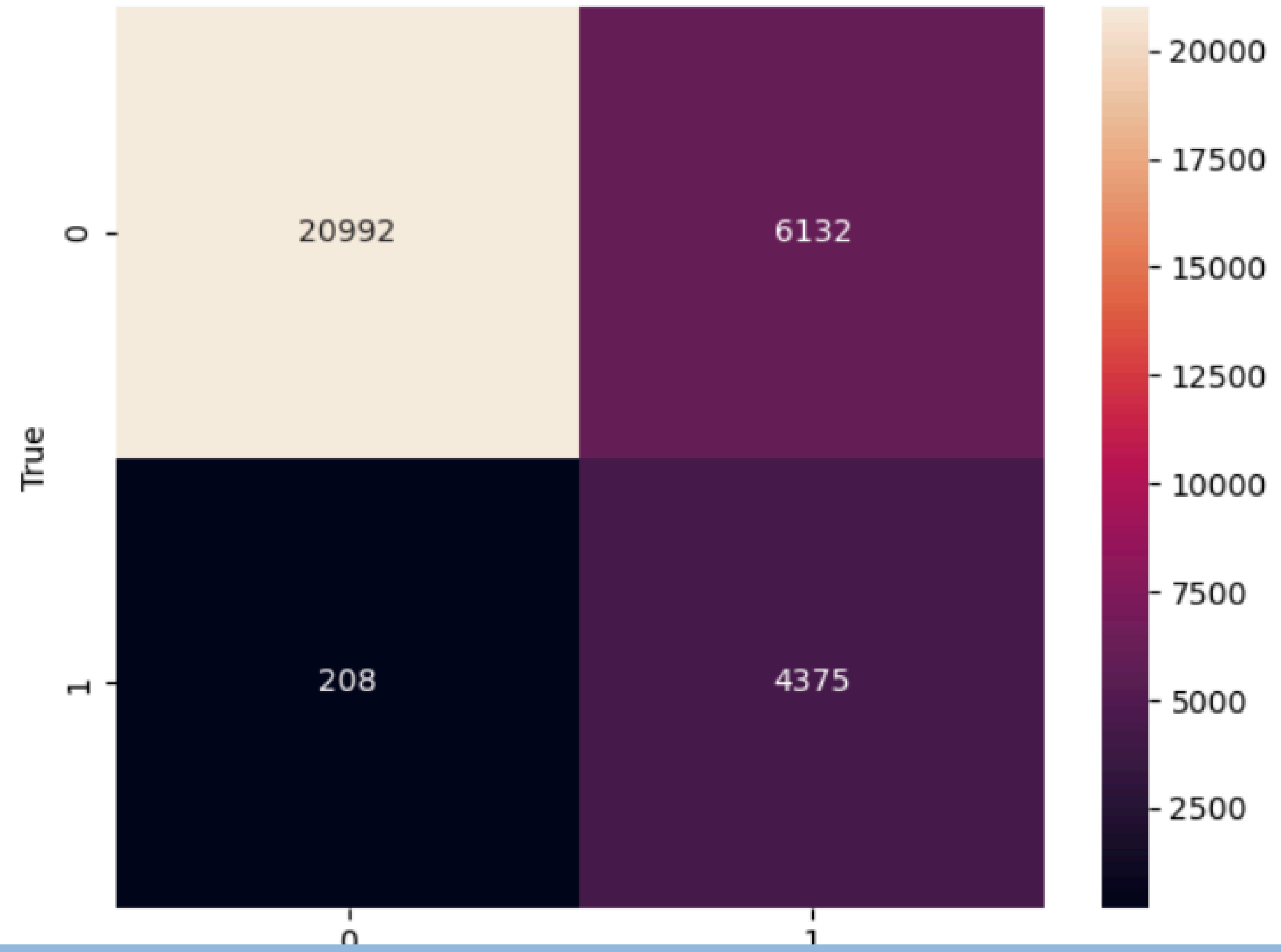
Class Imbalance
Our target variable is imbalanced:
most orders are not cancelled (Status = 0)

Default Classifiers Are Biased
Both Logistic Regression and Random Forest focus on predicting the majority class to maximize accuracy.

Our Solution: Make the Model Sensitive

```
Goodness of Fit of Model: Test Dataset (Balanced, Threshold = 0.4)
Classification Accuracy :  0.8000
True Negative Rate      :  0.7739
True Positive Rate      :  0.9546
False Negative Rate     :  0.0454
False Positive Rate     :  0.2261
```

Test Dataset (Threshold = 0.4)



What Changed After Tuning?

Much Higher Recall
True Positive Rate improved from 69.8% → 95.5%
Model now catches almost all cancelled orders.

But at a Cost
False Positive Rate increased from 0.9% → 22.6%
Meaning: More non-cancelled orders are mistakenly flagged.

Good for Risk-Averse Businesses
This setting is ideal if the cost of a missed cancellation is higher than the cost of a false alarm.

eXtreme Gradient Boosting

Why we tried XGBoost?

- Known for high performance in many real-world prediction tasks
- Handles complex, non-linear feature interactions

What we found?

Models	Random Forest	XGBoost
Accuracy	94.84%	94.77%
Recall	69.78%	68.89%
True Negative Rate	99.08%	99.14%

XGBoost didn't lead to better results.

WHY?

- Data is structured & not very nonlinear
- Feature signals may already be captured by simpler models
- Random Forest is already a strong baseline

Model complexity ≠ better performance

Data matters more

What we learned?

Key Model Observations

- Logistic Regression is simple but effective → good baseline
- Random Forest performed best even before tuning
- XGBoost didn’t outperform → complexity ≠ better

Optimization Insights

- Tuning (threshold + class_weight) helps maximize recall
- Best model choice depends on business goals
- Imbalanced target affects all models → accuracy ≠ everything

Project Outcomes

Using Our ML Model, Sellers Can:

For risk-averse platforms

Use the **balanced model** with a lower threshold.

-Catches almost all cancelled orders
-Accepts some false alarms

where cancellation losses outweigh the cost of intervention

Example: **luxury** e-commerce platforms

For cost-sensitive platforms

Use the **unweighted (default)** model

– Fewer false positives, more accurate overall
– May miss some cancellations

Ideal for cost-sensitive platforms,
with limited resources for manual intervention

Example: **fast-moving** consumer goods

Conclusion

- *Data-Driven Insights*
- *Recommendations*

Conclusion

Data-Driven Insights

High Order Amount ➔ Lower Cancellation
Customers placing larger orders tend to cancel less often, indicating stronger purchase intent.

Fulfilment Method Matters
Merchant fulfilment shows higher cancellation rates—likely due to delays or service issues.

Promotion Usage Helps
Orders with promotions show lower cancellation rates, possibly driven by stronger incentives or urgency.

Recommendations

Predict and Prevent with RF-Model
Use a trained Random forest ML model to flag high-risk orders early and trigger proactive follow-up by customer service.

Improve Fulfilment Reliability
Optimize logistics for high-risk fulfilment types to reduce delays and cancellations.

Targeted Promotions for High-Risk Categories
Offer time-limited discounts or free shipping to reduce cancellations in vulnerable product categories.

Thank you

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