Hotel Bookings Cancellation Predictions

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Context

- ➔ Cancellations = Revenue Loss

- ➔ How do you mitigate this?
  - ◆ Cancellation policy ☒
  - ◆ Overbooking ☒
  - ◆ Incentives ✅

Problem Statement

- How can a hotel reduce their revenue loss by 20% for next year by targeting customers that are likely to cancel with incentives to retain their reservation?

- **There is approximately €34,446,903 worth of potential revenue if all of the bookings are successful. The cancellations account for about 33% of that, which is a significant loss.**

€11,478,718 LOSS

Of the 4,784 canceled bookings in the test set,

76%

are correctly predicted to cancel

The Data

Two Hotels in Portugal:

1) Hotel 1(Resort): 40,060 rows
2) Hotel 2(City): 79,330 rows
3) Bookings are between 2015-2017

After Cleaning:

- 86,207 rows
- 19 features (28 after one-hot encoding)

Training and Testing:

- Train Set: 68,965 rows
- Test Set: 17,242 rows

[Reference: https://www.sciencedirect.com/science/article/pii/S2352340918315191#bib4]

Features:

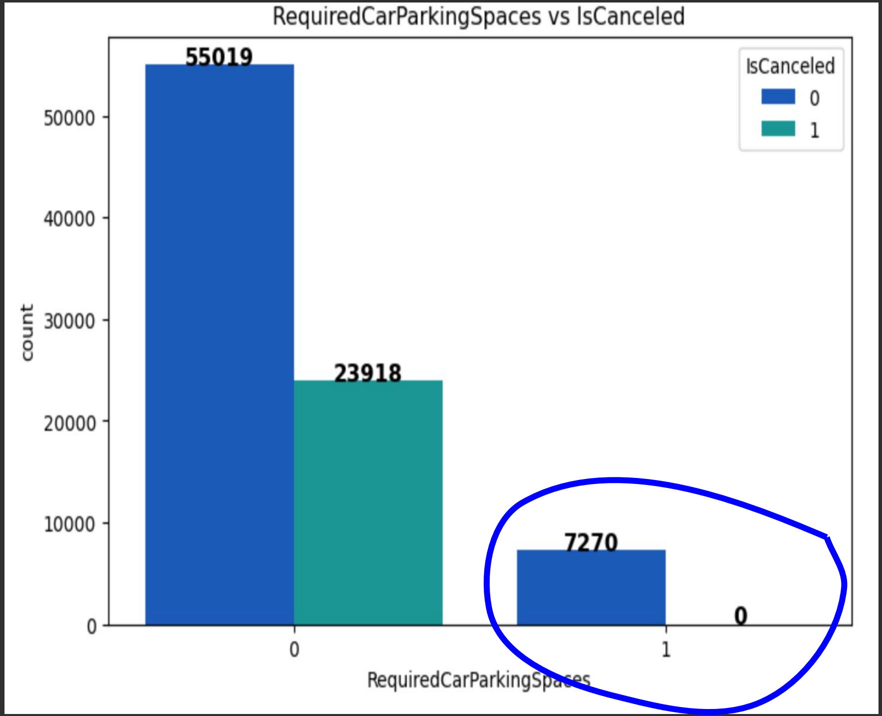
Car Spaces

Binary:

0 = No car space

1 = Car space

- 8% of bookings required a space
  - 0 cancellations

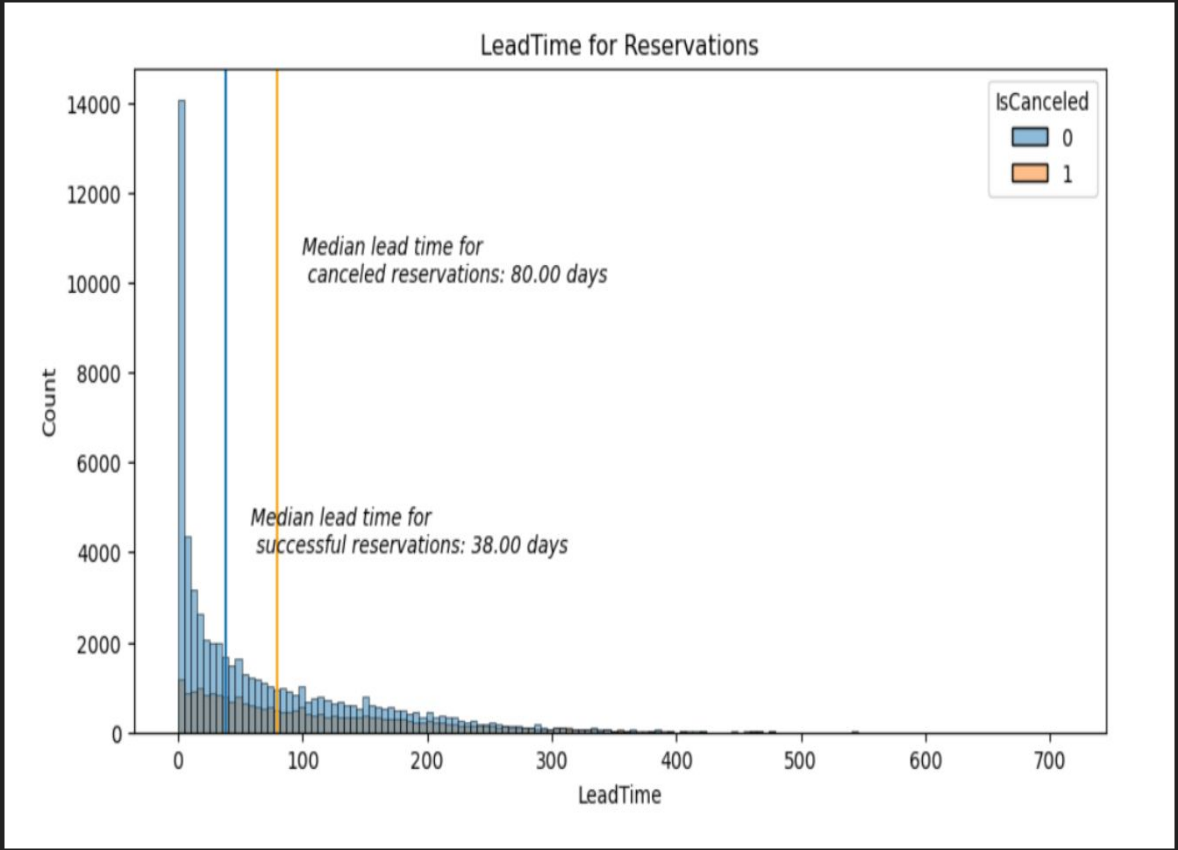


Lead Time

Number of days between reservation and arrival

<u>Median Lead Time:</u>

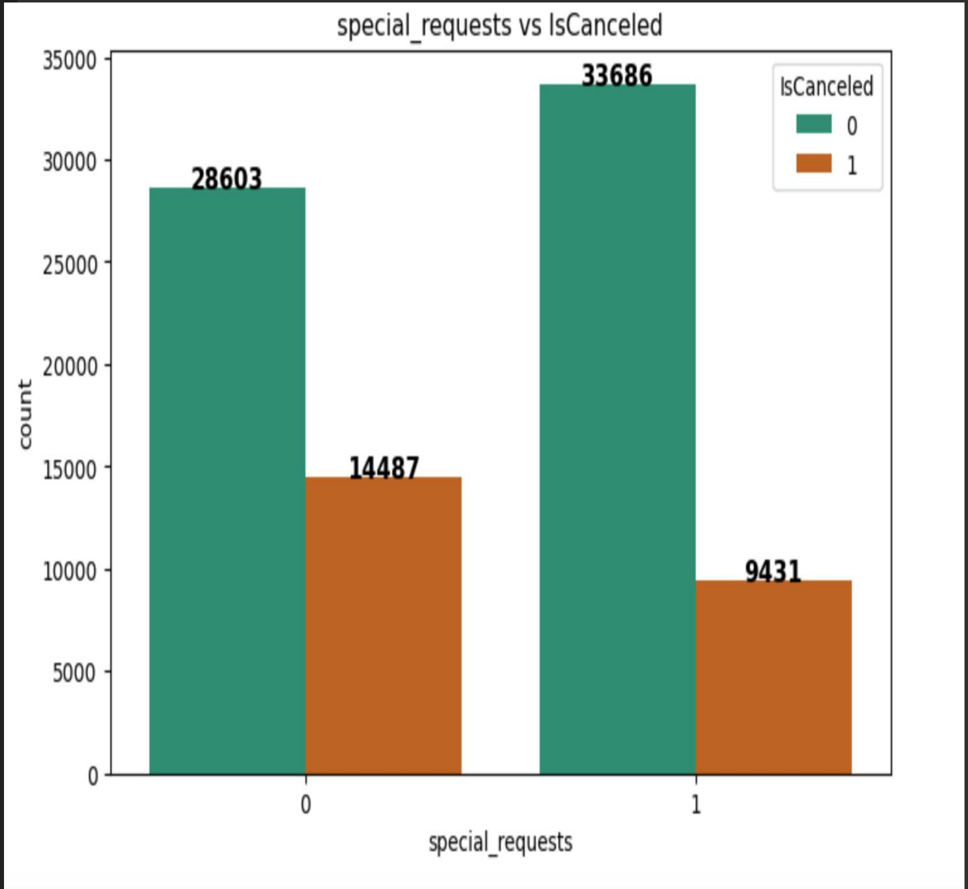
- **Canceled: 80 days**
- **Successful: 38 days**



Special Requests

Binary:
0 = No requests
1 = Requests

- Approximately 50/50 split between groups
- No Requests: 34% canceled
- Requests: 22% canceled

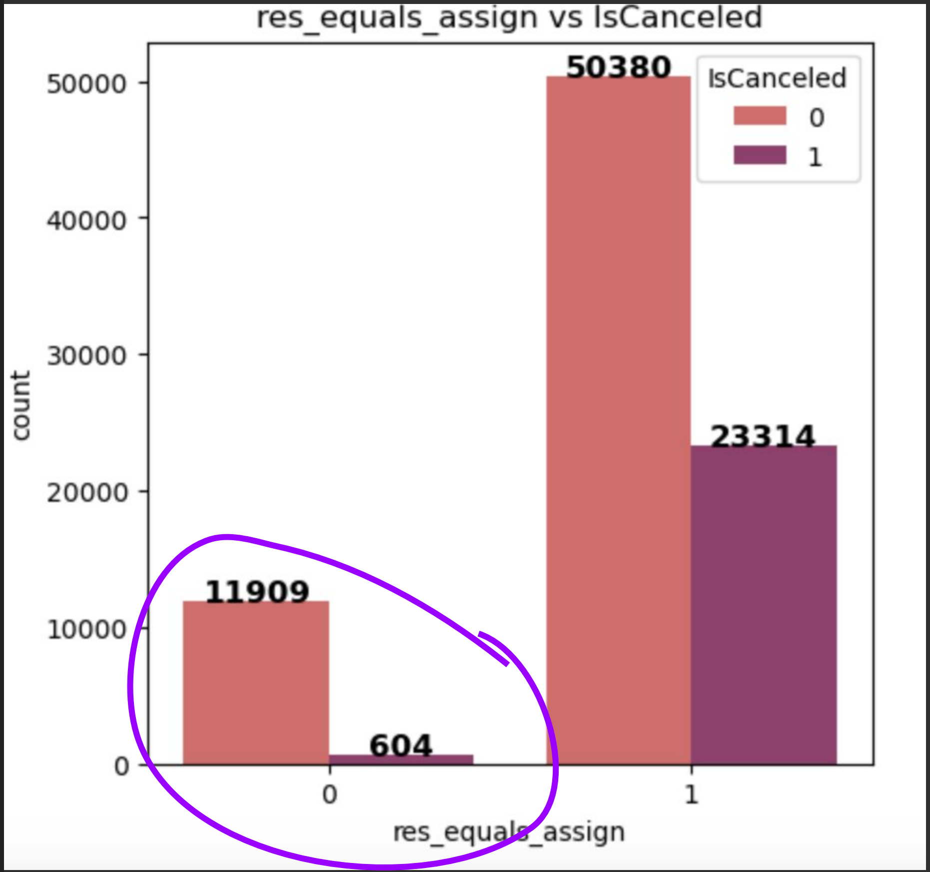


Reserved Room Type vs Assigned Room Type

Binary:

- 0 = Different Room Type
- 1 = Same Room type

➔ 14.5% of bookings received a different room type
  - Only 5% cancelled



Market Segment

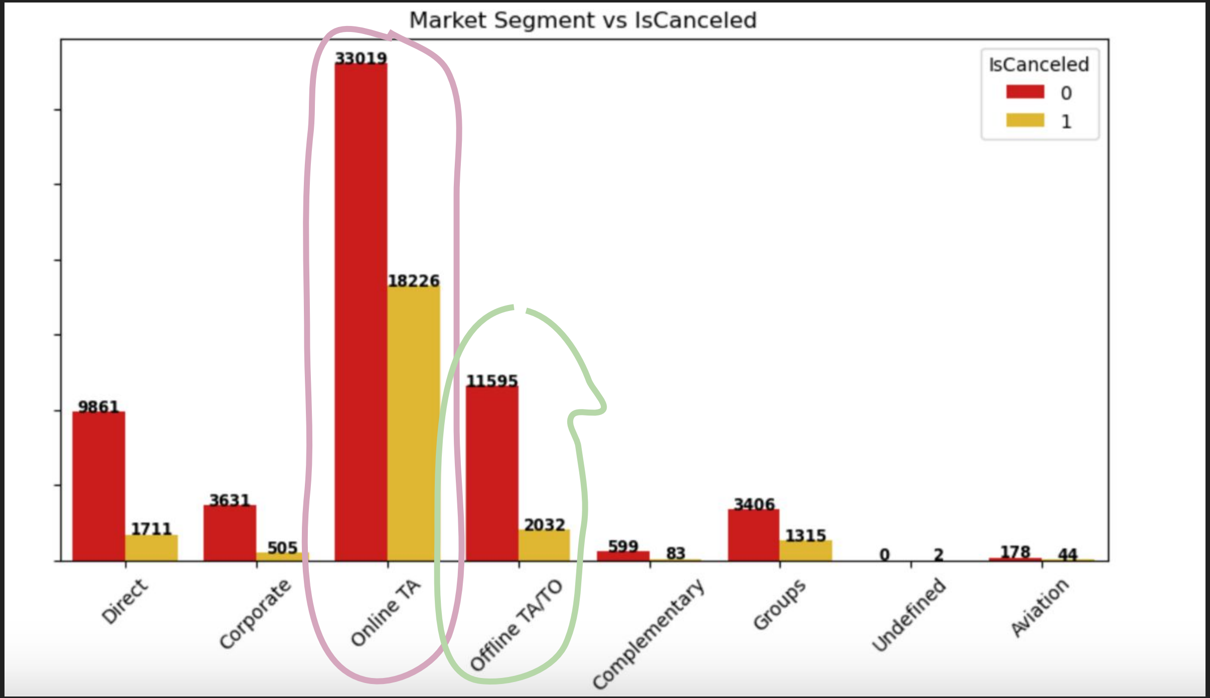
Categorical Feature

Online TA

- **59% of bookings**
  - **36% canceled**

Offline TA/TO

- **16% of bookings**
  - **15% canceled**



Agent Type

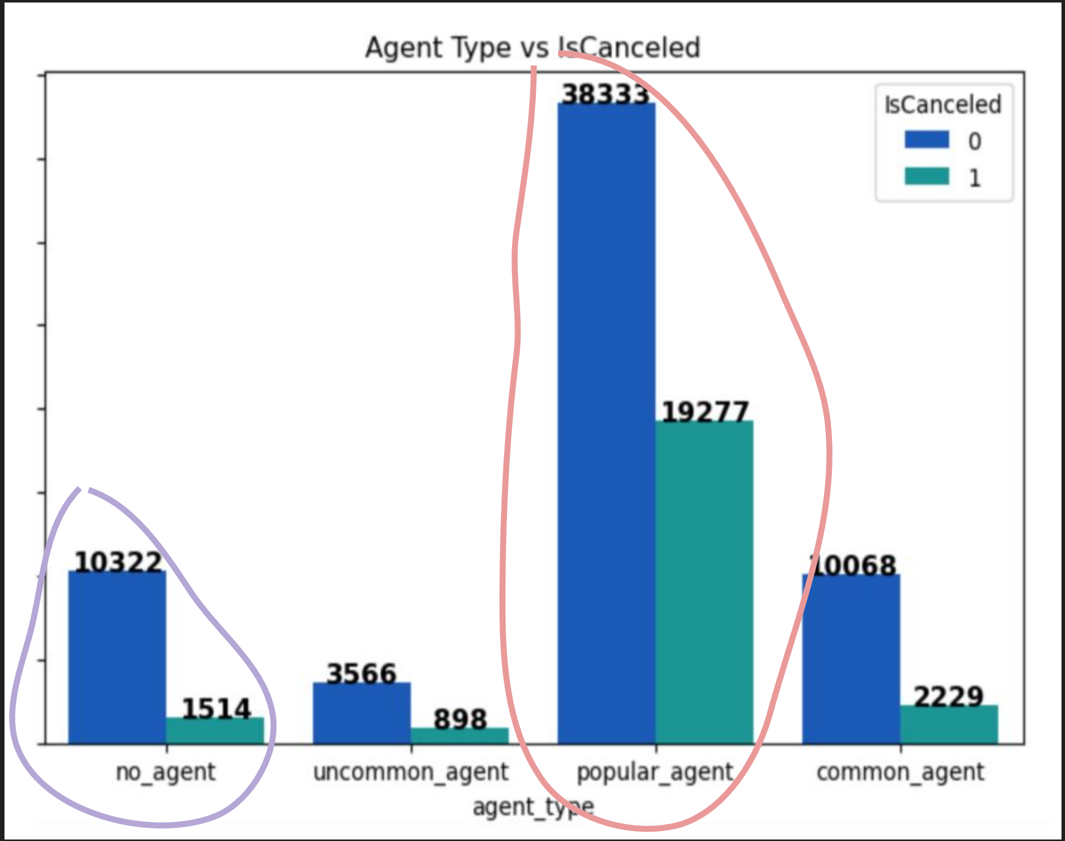
Categorical Feature:

Popular Agent:

- ➔ **66.8% of bookings**
  - ◆ **33.5% canceled**

No Agent:

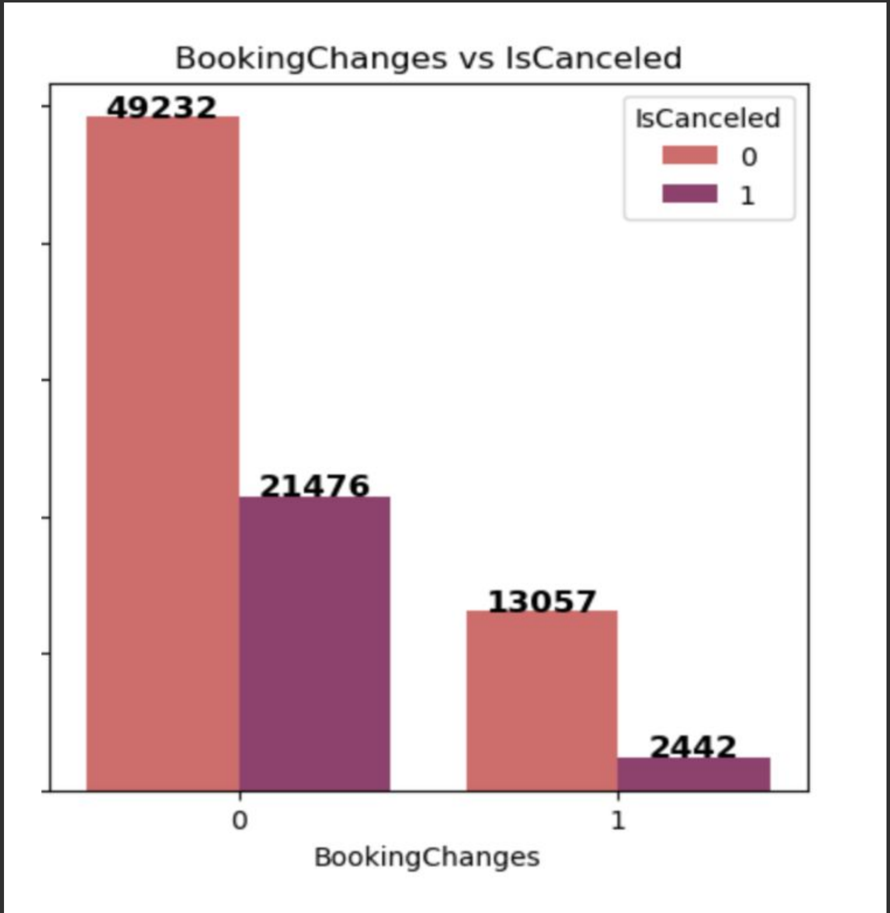
- ➔ **13.7% of bookings**
  - ◆ **12.8% canceled**



Booking Changes

Binary:
0 = No changes
1 = Changes

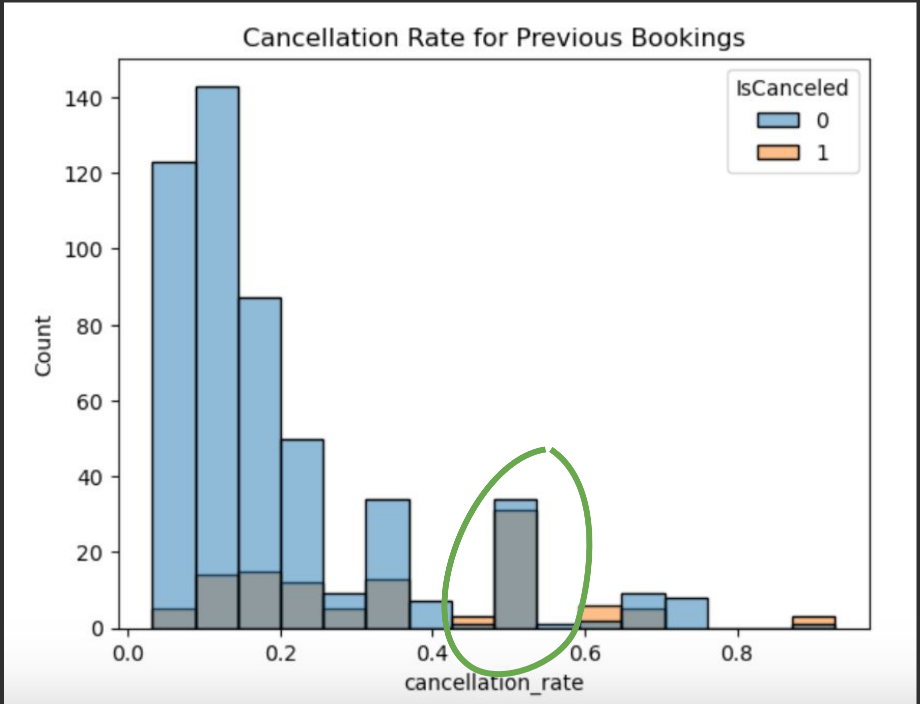
- ➔ No changes: 30% canceled
- ➔ Changes: 16% canceled



Previous cancellation rate

Group A: 0% PCR
- 98% are in this group
- 26% canceled

Group B: 100% PCR
- 1.2% are in this group
- 98% canceled AGAIN



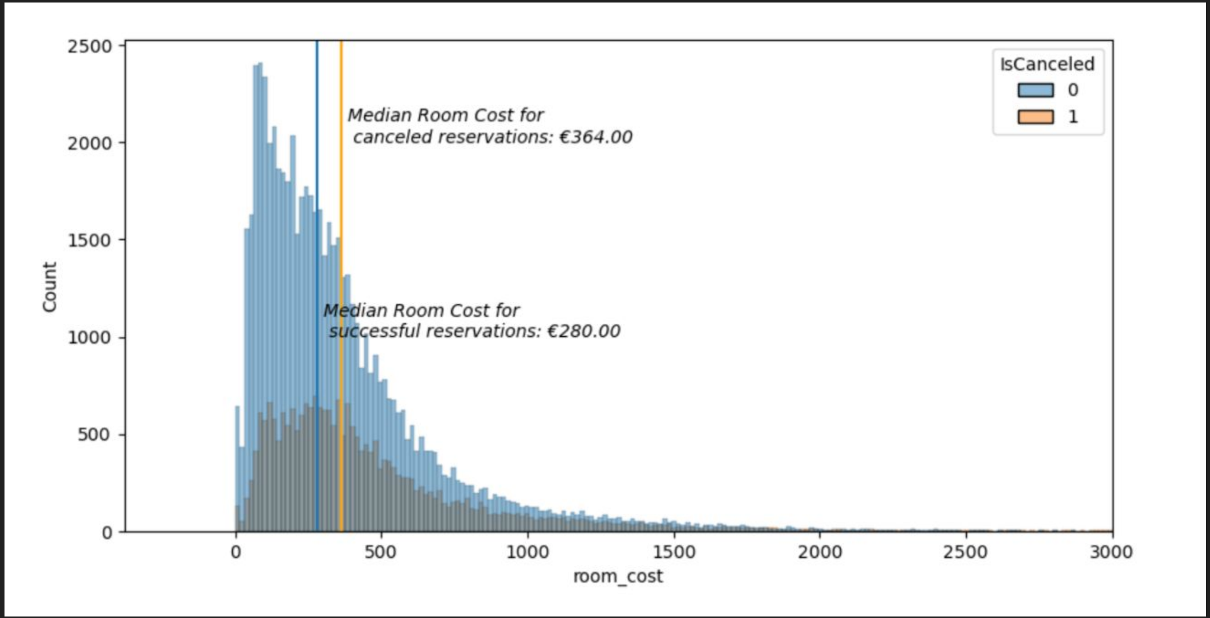
Group C: Everyone else
- 0.8% are in this group
- People who cancel previously, tend to cancel again

Room Cost

Total cost of the room

Median Room Cost:

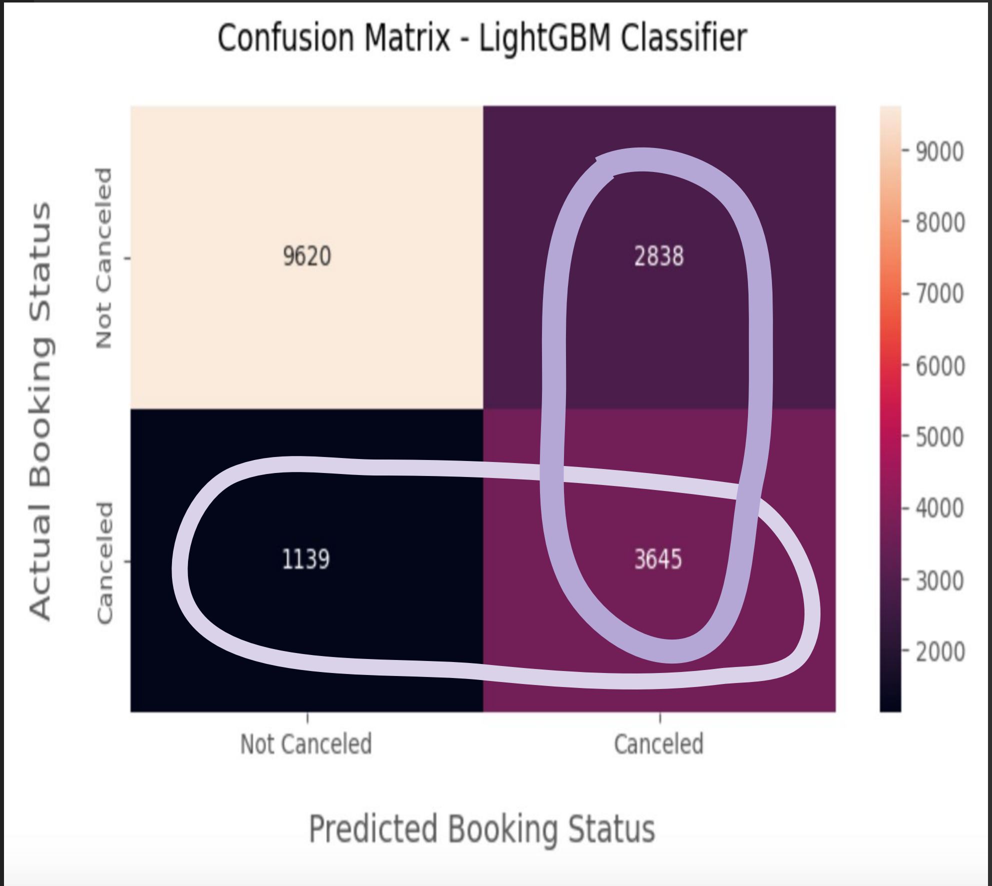
- **Canceled: €364**
- **Successful: €280**



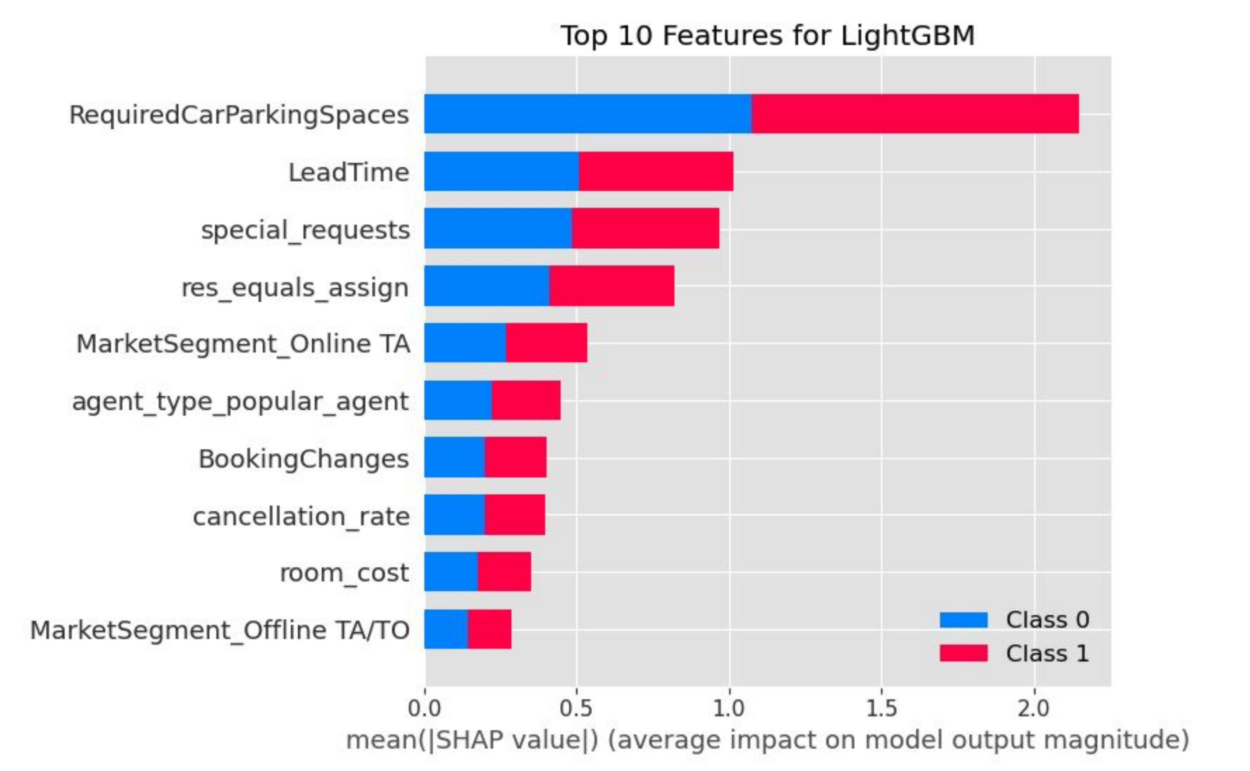
The Model

Recall: 76%

Precision: 56%



Important Features



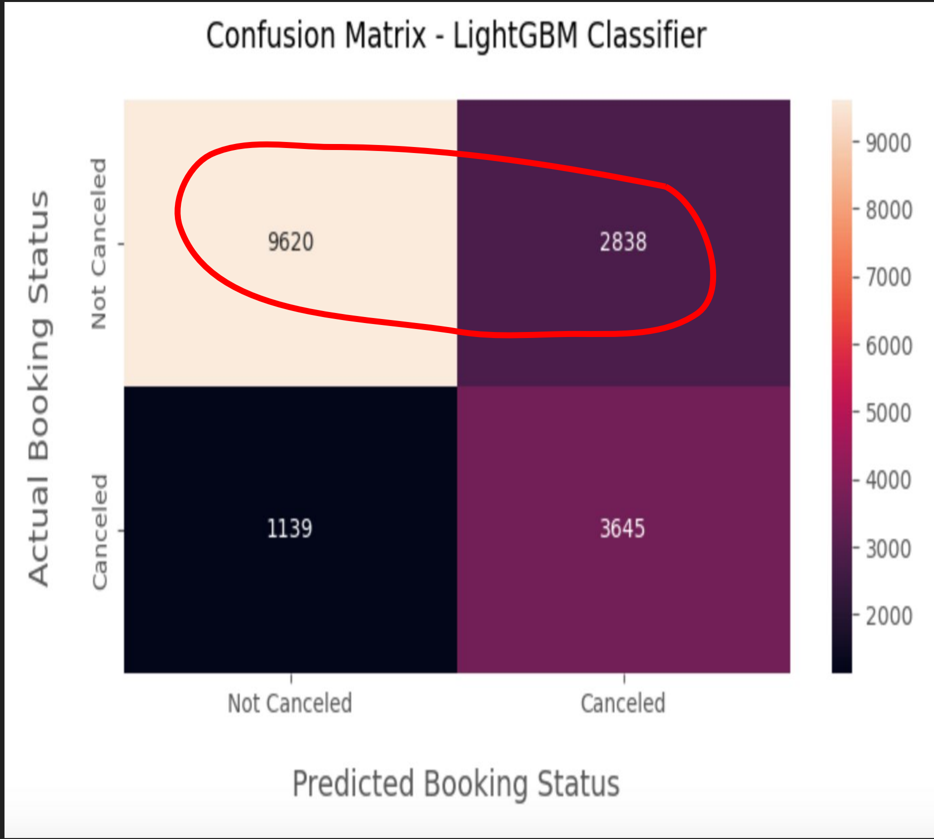
Are the False Positives an Issue? (No, but maybe)

- 12,458 Successful bookings
  - 2,838 are false positives (22.7%)

- Successful booking = revenue gain✅

- Booking retention could be costly❌
  - Complementary Rooms, meals, other services

  - Note: financial data not readily available to calculate profit.



Decision Threshold

	IsCanceled	predictions	probability_sucessful	probability_canceled
☒	0	1	0.412427	0.587573
✅	1	1	0.118317	0.881683
✅	0	0	0.949426	0.050574
☒	1	0	0.635925	0.364075
✅	0	0	0.701680	0.298320

Predictions in Practice

Bookings Predicted to Cancel:

1. **At least 70% probability**:
   a. Email/phone call to customer
   b. Offer Complimentary nights, meals, etc. (**if costs allow**)

2. **Less than 70% probability:**
   a. Email/phone call to customer

Further Work

1. Financial Data
    a. How many incentives can the hotel actually offer? (nights, meals, etc.)

2. Weather Forecast Data
    a. Could improve model accuracy