Predicting Hotel Booking Cancellations

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Context

Cancellations can have a significant impact on revenue in the hospitality industry. Many hotels implement cancellation policies or use overbooking strategies to mitigate the effect of this, but this can have a negative impact on revenue and reputation of the hotel. Developing a machine learning model to predict which bookings are more likely to cancel can help hotels to better strategize and use more appropriate techniques to mitigate the impact that cancellations have on revenue. Bookings that are more likely to cancel can be targeted with incentives to not cancel, such as complimentary meals, or extra nights.

Problem Statement

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

Data Wrangling

The data is from ScienceDirect, but was originally sourced from Property Management System SQL databases. Included in the data are 31 columns from two different hotels in Portugal. Hotel 1 has 40,060 observations and hotel 2 has 79,330, where each observation represents a hotel booking. The bookings span from 2015 until 2017. The target column 'IsCanceled' tells us if the reservation was canceled (1) or not (0).

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

Features:

- `Hotel`: Identifies which hotel the observations belongs to (h1:Resort Hotel, h2: City Hotel)
- `IsCanceled`: Target Variable. Indicates if booking was canceled (1) or not (0)
- `LeadTime` : Number of days that elapsed between the booking data and the arrival date
- `ArrivalDateYear` : Year of arrival date
- `ArrivalDateMonth` : Month of arrival date
- `ArrivalDateWeekNumber` : Week of arrival date
- `ArrivalDateDayOfMonth` : Day of month for arrival date
- `StaysInWeekendNights` : Number of weekend nights for booking
- `StaysInWeekNights` : Number of week nights for booking
- `Adults`: Number of adults
- `Children` : Number of children
- `Babies` : Number of babies
- `Meal` : Type of meal package
    - Undefined/SC – no meal package;
    - BB – Bed & Breakfast;
    - HB – Half board (breakfast and one other meal – usually dinner);
    - FB – Full board (breakfast, lunch and dinner)
- `Country` : Country of origin. Categories are represented in the ISO 3155–3:2013 format
    - i.e. 'IRL' is Ireland, 'ESP' is Spain, etc
- `MarketSegment` : Market segment designation. In categories, the term “TA” means “Travel Agents” and “TO” means “Tour Operators”
- `DistributionChannel` : Booking distribution channel. The term “TA” means “Travel Agents” and “TO” means “Tour Operators”
- `IsRepeatedGuest` : Value indicating if the booking name was from a repeated guest (1) or not (0)
- `PreviousCancellations` : Number of previous bookings that were canceled by the customer prior to the current booking
- `PreviousBookingsNotCanceled` : Number of previous bookings not canceled by the customer prior to the current booking
- `ReservedRoomType` : Code of room type reserved. Code is presented instead of designation for anonymity reasons
- `AssignedRoomType` : Code for the type of room assigned to the booking. Sometimes the assigned room type differs from the reserved room type due to hotel operation reasons (e.g. overbooking) or by customer request. Code is presented instead of designation for anonymity reasons

- `BookingChanges` : Number of changes/amendments made to the booking from the moment the booking was entered until the moment of check-in or cancellation
- `DepositType` : Indication on if the customer made a deposit to guarantee the booking. This variable can assume three categories:
    - No Deposit – no deposit was made
    - Non Refund – a deposit was made in the value of the total stay cost
    - Refundable – a deposit was made with a value under the total cost of stay.
- `Agent` : ID of the travel agency that made the booking
- `Company` : ID of the company/entity that made the booking or responsible for paying the booking. ID is presented instead of designation for anonymity reasons
- `DaysInWaitingList` : Number of days the booking was in the waiting list before it was confirmed to the customer
- `CustomerType` : Type of booking, assuming one of four categories:
    - Contract - when the booking has an allotment or other type of contract associated to it;
    - Group – when the booking is associated to a group;
    - Transient – when the booking is not part of a group or contract, and is not associated to other transient booking;
    - Transient-party – when the booking is transient, but is associated to at least other transient booking
- `ADR` : Average Daily Rate
- `RequiredCarParkingSpaces` : Number of car parking spaces required by the customer
- `TotalOfSpecialRequests` : Number of special requests made by the customer (e.g. twin bed or high floor)
- `ReservationStatus` : Reservation last status, assuming one of three categories:
    - Canceled – booking was canceled by the customer;
    - Check-Out – customer has checked in but already departed;
    - No-Show – customer did not check-in and did inform the hotel of the reason why
- `ReservationStatusDate` : Date at which the last status was set. This variable can be used in conjunction with the ReservationStatus to understand when was the booking canceled or when did the customer checked-out of the hotel

Missing Values:

- ➔ `Children: 4 rows replaced with 0`
- ➔ `Country: 488 rows replaced with 'unknown'`

Duplicate Rows:

- ➔ **31994** duplicate rows were removed

More rows removed:

- ➔ **166** rows have 0 adults and 0 children
- ➔ **591** rows have 0 weeknights and 0 weekend nights
- ➔ **432** rows have 0 ADR (these exclude bookings grouped as complementary)

After data wrangling and cleaning, we are left with **86207 rows** and **34 features**.

Exploratory Data Analysis

Numerical Data:

	count	mean	std	min	25%	50%	75%	max
IsCanceled	87396.0	0.274898	0.446466	0.00	0.0	0.0	1.0	1.0
LeadTime	87396.0	79.891368	86.052325	0.00	11.0	49.0	125.0	737.0
ArrivalDateYear	87396.0	2016.210296	0.686102	2015.00	2016.0	2016.0	2017.0	2017.0
ArrivalDateWeekNumber	87396.0	26.838334	13.674572	1.00	16.0	27.0	37.0	53.0
ArrivalDateDayOfMonth	87396.0	15.815541	8.835146	1.00	8.0	16.0	23.0	31.0
StaysInWeekendNights	87396.0	1.005263	1.031921	0.00	0.0	1.0	2.0	19.0
StaysInWeekNights	87396.0	2.625395	2.053584	0.00	1.0	2.0	4.0	50.0
Adults	87396.0	1.875795	0.626500	0.00	2.0	2.0	2.0	55.0
Children	87396.0	0.138633	0.455871	0.00	0.0	0.0	0.0	10.0
Babies	87396.0	0.010824	0.113597	0.00	0.0	0.0	0.0	10.0
IsRepeatedGuest	87396.0	0.039075	0.193775	0.00	0.0	0.0	0.0	1.0
PreviousCancellations	87396.0	0.030413	0.369145	0.00	0.0	0.0	0.0	26.0
PreviousBookingsNotCanceled	87396.0	0.183990	1.731894	0.00	0.0	0.0	0.0	72.0
BookingChanges	87396.0	0.271603	0.727245	0.00	0.0	0.0	0.0	21.0
DaysInWaitingList	87396.0	0.749565	10.015731	0.00	0.0	0.0	0.0	391.0
ADR	87396.0	106.337246	55.013953	-6.38	72.0	98.1	134.0	5400.0
RequiredCarParkingSpaces	87396.0	0.084226	0.281533	0.00	0.0	0.0	0.0	8.0
TotalOfSpecialRequests	87396.0	0.698567	0.831946	0.00	0.0	0.0	1.0	5.0

Categorical Data:

	count	unique	top	freq
Hotel	87396	2	h2	53428
ArrivalDateMonth	87396	12	August	11257
Meal	87396	5	BB	67978
Country	87396	178	PRT	27453
MarketSegment	87396	8	Online TA	51618
DistributionChannel	87396	5	TA/TO	69141
ReservedRoomType	87396	10	A	56552
AssignedRoomType	87396	12	A	46313
DepositType	87396	3	No Deposit	86251
Agent	87396	334	9	28759
Company	87396	353	NULL	82137
CustomerType	87396	4	Transient	71986
ReservationStatus	87396	3	Check-Out	63371
ReservationStatusDate	87396	926	2016-02-14	211

The initial look at the descriptive statistics of the features reveals some issues that need to be explored further:

- ➔ **ADR** has a minimum value of -6.38
  - ◆ This value was replaced with 57.32 (the mean ADR for bookings within a similar group)
- ➔ The most common **Company** is NULL
  - ◆ 94% of the rows are within the NULL group, so we will be dropping this column
- ➔ The number of unique room types differs for **AssignedRoomType** and **ReservedRoomType**
  - ◆ There are 2 extra room types in AssignedRoomType. The room types are coded, so there is no way to know what the actual room types are.

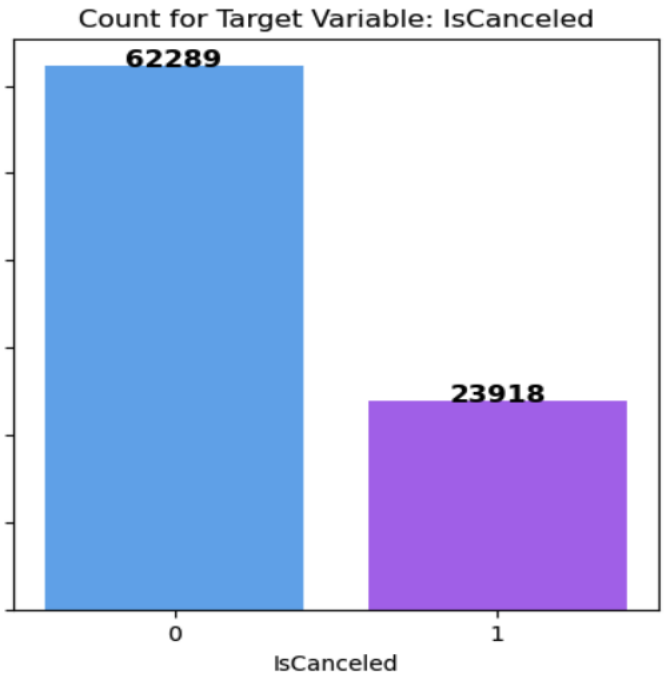
Feature Engineering:

- ☐ **Continent**: country codes were extracted from wikipedia and were used to group the countries into continents
- ☐ **is_europe**: binary feature identifying if a booking is from europe (1) or not (0)
- ☐ **total_people**: the sum of adults, children, and babies
- ☐ **total_nights**: the sum of weekend nights and weeknights
- ☐ **cancellation_rate**: PreviousCancellations and PreviousBooksingsNotCanceled combined $PC/(PC + PBNC)$
- ☐ **res_equals_assign**: binary feature where reserved room type is the same as assigned room type (1) or not (0)
- ☐ **agent_type**: agents are grouped into 4 groups
    1. no agent
    2. uncommon agent (100 or less bookings)
    3. common agent (between 101 and 999 bookings)
    4. popular agent (1000 or more bookings)
- ☐ **wait_list**: binary feature identifying if booking is on a wait list (1) or not (0)
- ☐ **special_requests**: binary feature identifying if booking has special request (1) or not (0)
- ☐ **room_cost**: Product of ADR and total_nights

Features removed:

- ➔ `ArrivalDateYear` (irrelevant feature)
- ➔ `Country` (replaced by Continent and is_europe)
- ➔ `Adults, Children,Babies` (replaced by total_people)
- ➔ ReservedRoomType, AssignedRoomType (replaced by res_equals_assgn)
- ➔ Agent (replaced by agent_type)
- ➔ Company (using MarketSegment instead of Company)
- ➔ `ReservationStatus, ReservationStatusDate`
- ➔ DaysInWaitingList (replaced by wait_list)
- ➔ TotalOfSpecialRequests (replaced by special_requests)

Target: IsCanceled



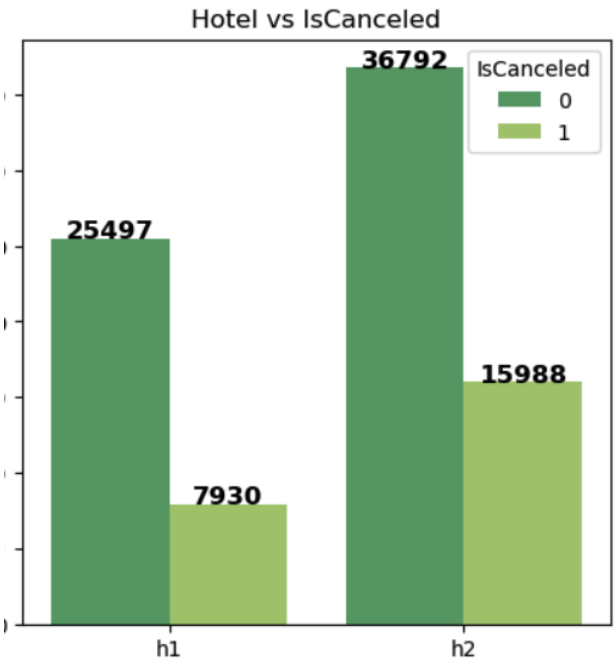
The target variable has:

- ➔ **62,2289 successful bookings**
- ➔ **23,918 canceled bookings.**

This ***class imbalance*** will be something to keep in mind during modeling.

Exploring Features and Target Relationships:

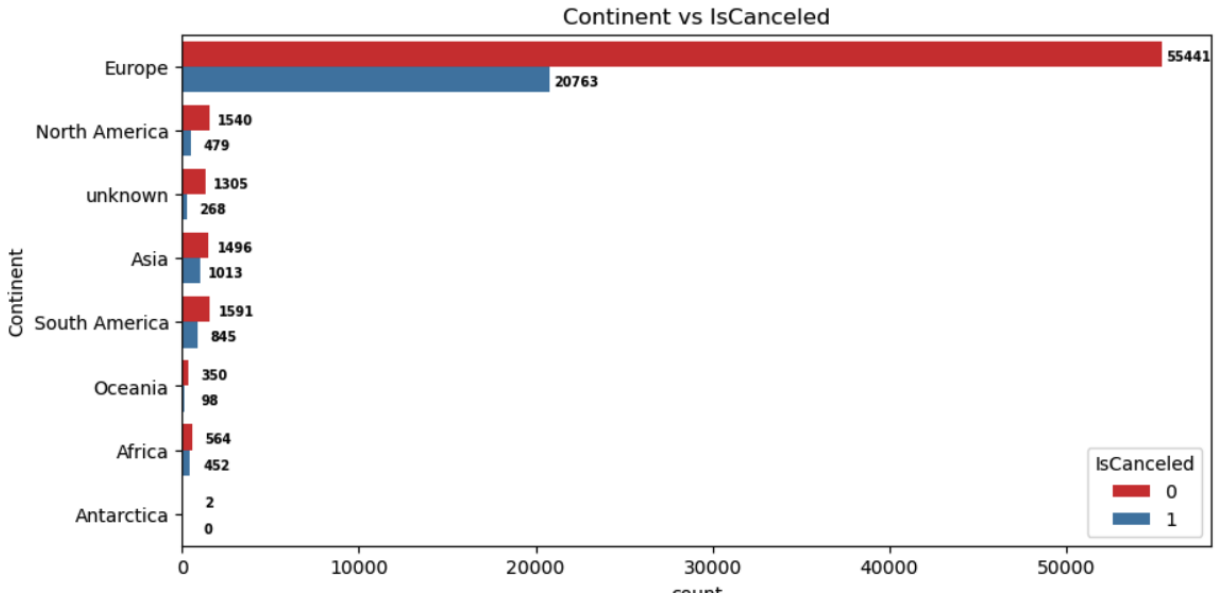
1) Hotel



- ➔ Hotel 1: 24% are canceled
- ➔ Hotel 2: 30% are canceled

Hotel 2 (city) has more bookings overall, but it also has a higher rate of cancellations than hotel 1 (resort)

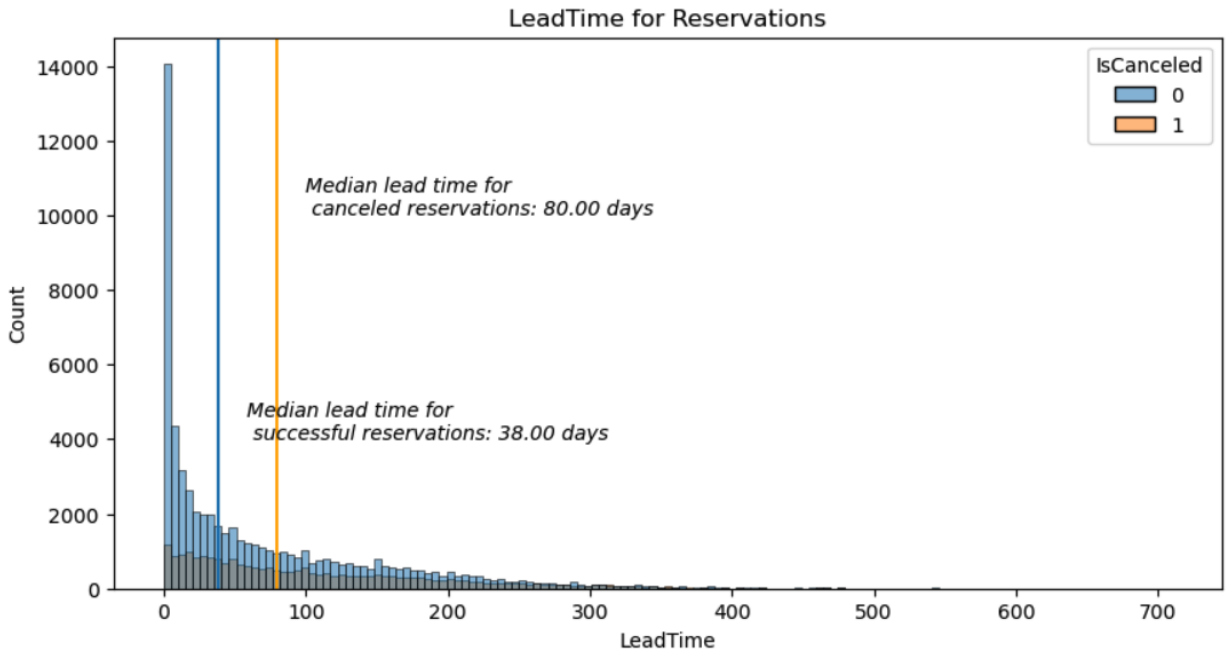
2) Continent and is_europe



88% of bookings are customers from Europe, which is expected since the hotels are located in Europe (Portugal). However, the highest proportion of customer cancellations comes from other continents. **32% of customers** not from Europe are canceled, while only **27% of the customers** who are from Europe canceled.

% of cancellations within each Continent	
Africa	**44%**
Asia	**40%**
South America	34%
Europe	**27%**
North America	24%
Oceania	22%
Unknown	17%
Antarctica	0%

3) LeadTime



The lead time for bookings is highly skewed to the right, with the majority of bookings having a lead time between 0 and 200 days. The skew suggests some heavy outliers, with a maximum lead time of 737 days. The outliers here will not be removed, as they may provide insights into cancellations for reservations booked far in advance.

- ➔ For **canceled bookings**, the median lead time is **80 days**.
- ➔ For **successful bookings**, the median lead time is **38 days**.

This intuitively makes sense, as the more time in between the reservation and the day of arrival, the more likely something can occur that would result in having to cancel a reservation.

4) total_people

Number of People in Booking	% of total Bookings	% of Cancellations for group
1	**18.12%**	**20%**
2	**65.62%**	**28%**
3	**11.63%**	**31%**
4	4.46%	**42%**
5	**0.15%**	**23%**
10	**0.0023%**	**0%**
12	**0.0012%**	**50%**

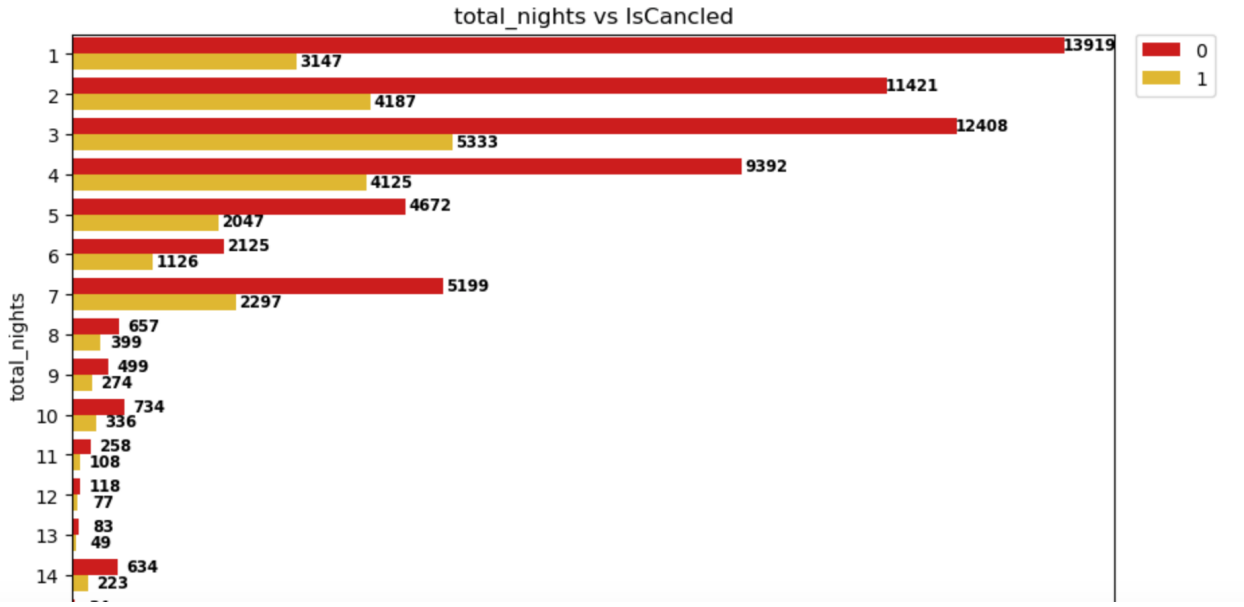
- ➔ The bookings have either 1, 2, 3, 4, 10, or 12 people with about **95%** of the bookings being in the **1, 2**, or **3 person groups**.

- ➔ Reservations in those groups cancel **20%**, **28%**, and **31%** of the time respectively.

- ➔ Bookings with **4 people** account for **4.46%** of the total bookings, but **cancel 42% of the time.**

Bookings with **more than 4 people account for less than 1% of the total bookings,** so we cannot draw many insights from them. However, we can see that as the number of people in the booking increases, the probability of cancelation increases.

5) total_nights and is_weekend



➔ The number of total nights ranges from 1 to 69, with the majority of bookings being less than 15 nights.

➔ The **median** for both the canceled and successful reservations is **3 days**.

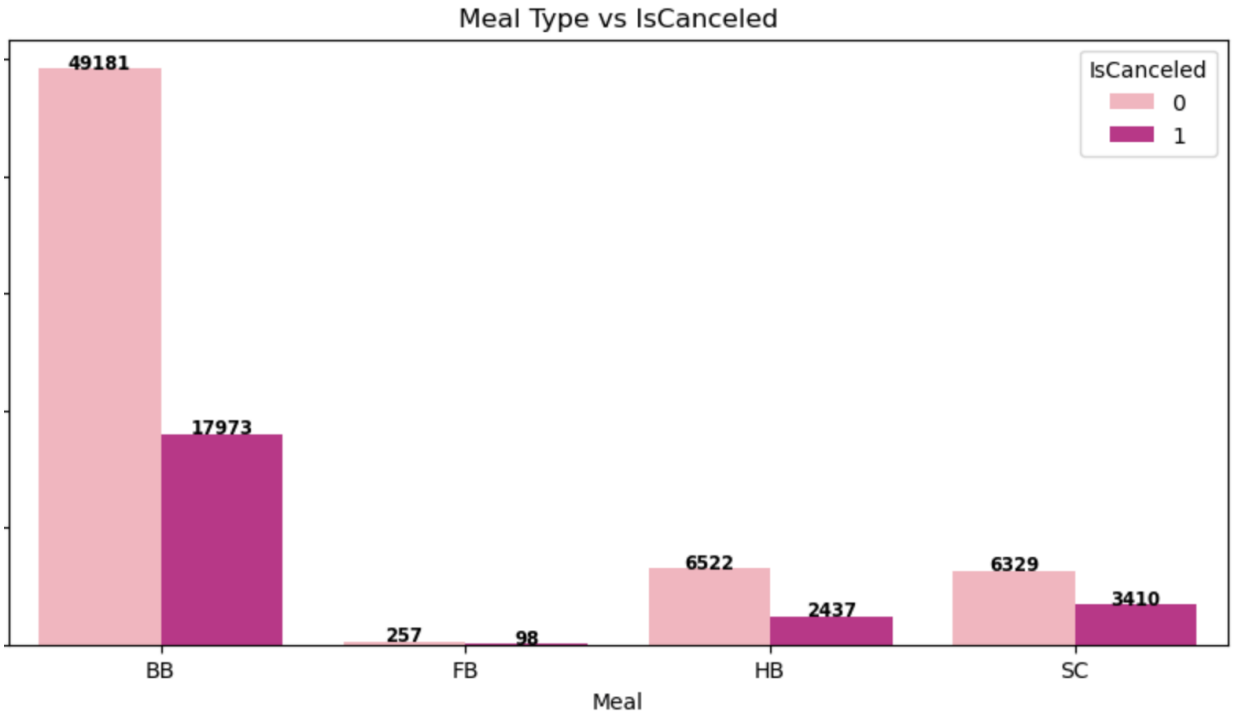
➔ As the number of nights increases, the higher the percentage of cancellations within that group:

- 1 night = 18.4% canceled
- 2 nights = 26.8% canceled
- 3-7 nights ≃ 30% canceled
- 8-9 nights ≃ 36% canceled
- 10-11 nights ≃ 30% canceled
- **12-13 nights ≃ 38% canceled**

★ 60% of reservations are on **weekend nights**, and they **cancel 29.4% of the time.**

★ 40% of reservations are on **weeknights**, and **cancel 25.2% of the time.**

6) meal

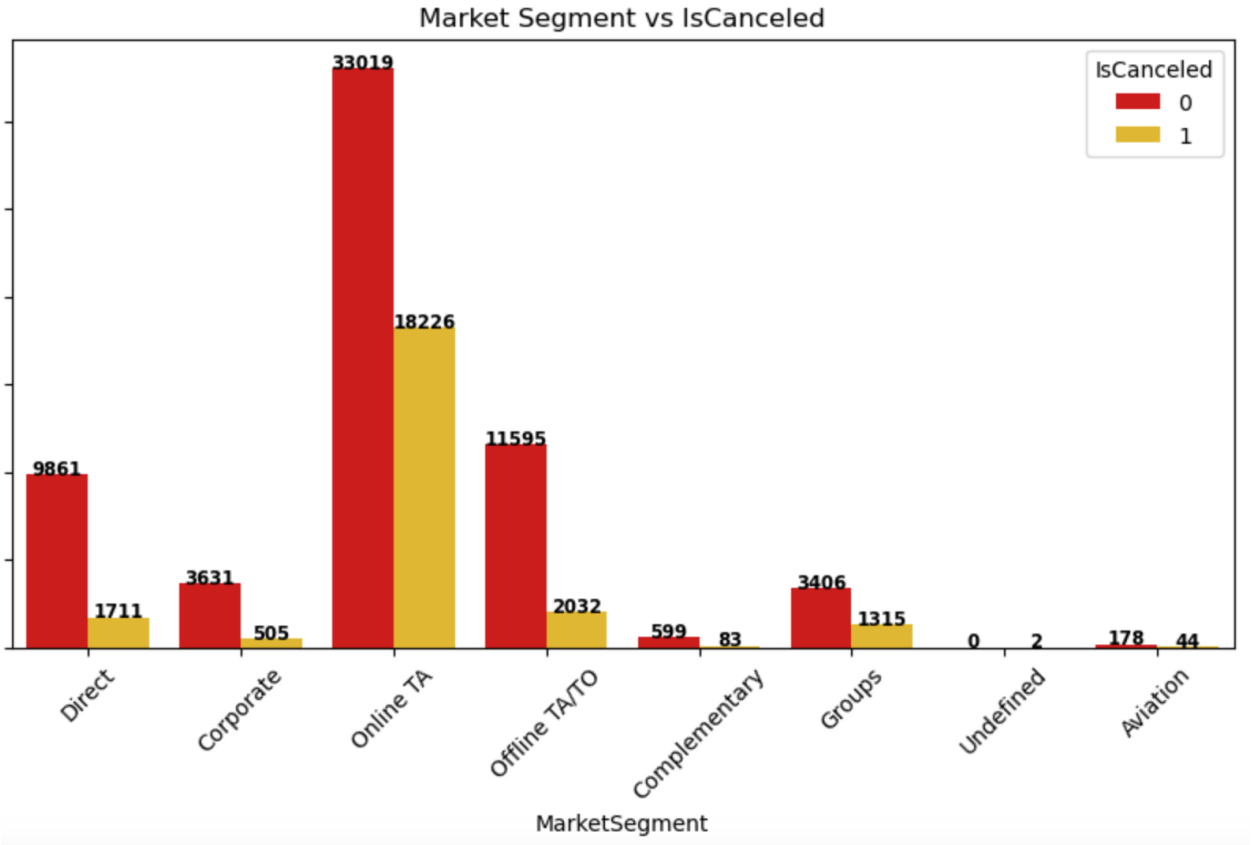


➔ The bookings with meal types of BB, FB, and HB all cancel approximately 26-27% of the time, while the **meal type of SC (no meal plan) cancels 35% of the time.**

➔ To reduce the number of groups, we will binarize this feature (has meal = 1, no meal = 0)

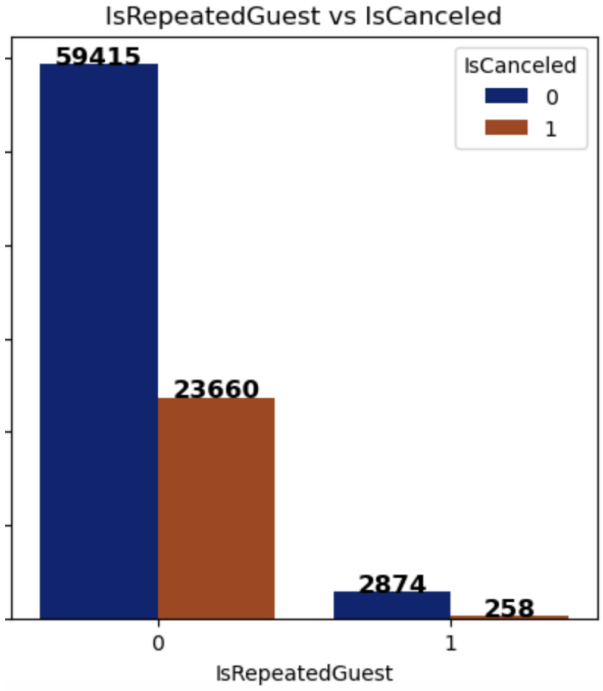
7) MarketSegement and CustomerType

Since the market segment and customer type give almost the same information, we will only be focusing on the market segment to avoid any redundancy or collinearity between features.



- ➔ The biggest takeaway from analyzing market segments is that bookings in the **Online TA market segment** account for the majority of the bookings, and also have the highest percentage of cancellations, with **36% of the bookings canceled**.
- ➔ 5% are in the **Groups** segment: **28% cancel.**
- ➔ 16% are in the **offline TA/TO** segment: **only 15% cancel.**

8) IsRepeatedGuest and canellation_rate



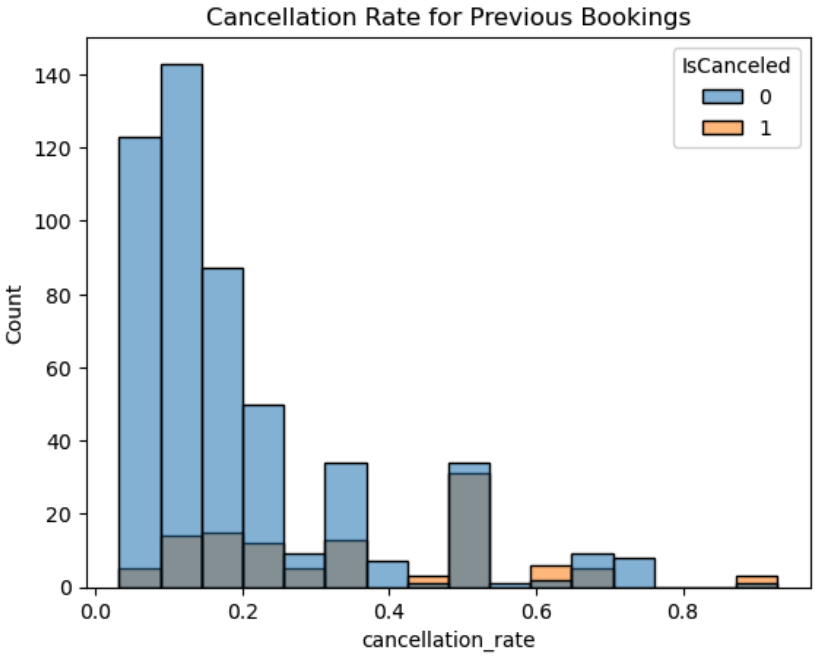
➔ 96% of bookings come from **new guests.**

- **28% canceled**

➔ The other 4% are **repeat guests**.

- Only **8% canceled**

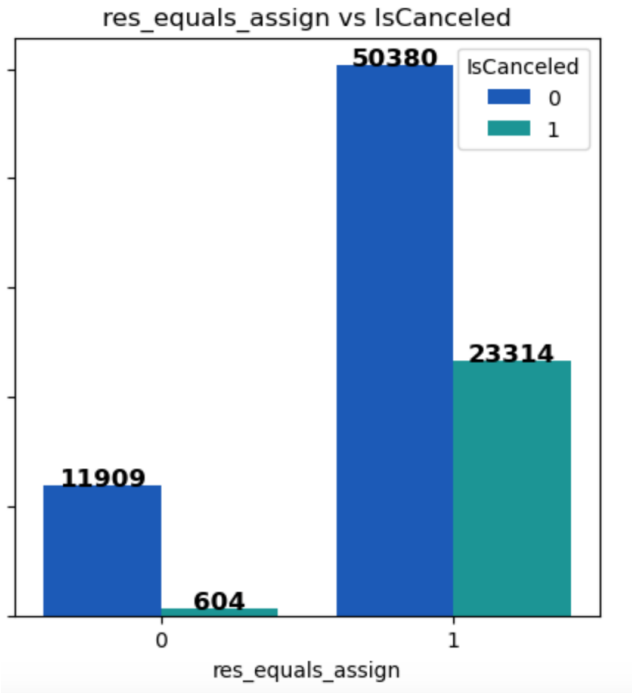
The **cancellation_rate** feature was created from previous booking information. Since 96% of the bookings are new guests, we are not surprised by the fact that 98% of bookings have a previous cancellation rate of 0%, and 1.2% have a rate of 100%.



The histogram shows the distribution of the cancellation rate between 0 and 100%.

➔ Bookings that have a previous cancellation rate of approximately 50%, are very likely to cancel.

9) res_equals_assign



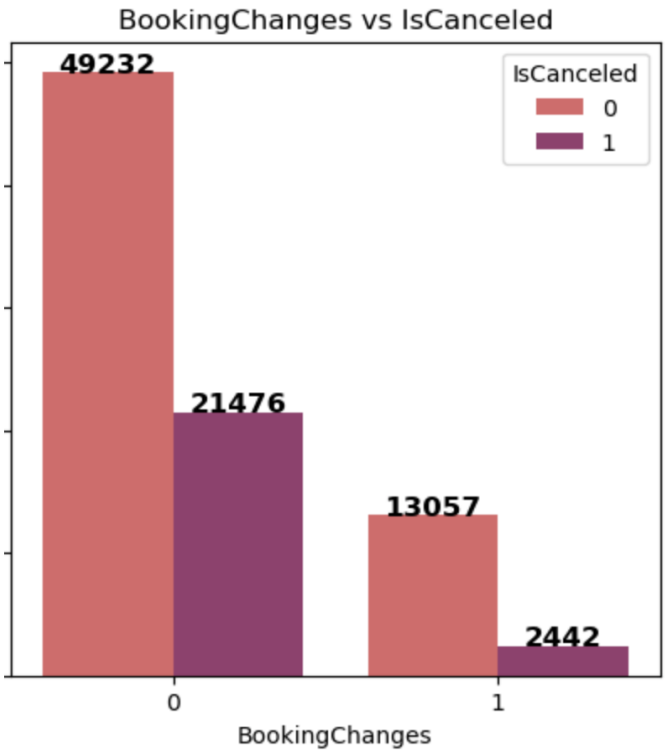
➔ 85% of the bookings received the same room type that was originally requested, and they cancel 32% of the time.

➔ **15% of bookings did not receive the same room type, and only canceled 5% of the time.**

This intuitively makes sense and is quite insightful. The most likely explanation for this group canceling less is that they may have received a room upgrade, which would incentivize the customer to not cancel.

10) booking_changes

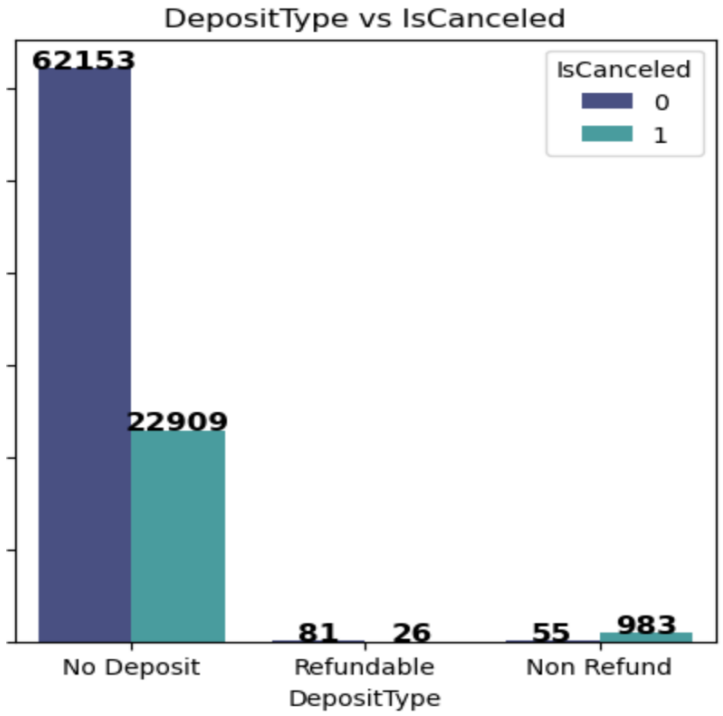
82.02% of the bookings did not request any changes to their reservation, 12.35% requested only a single change, and 3.9% requested two changes. The number of changes ranges from 1 up to a maximum of 18 changes, but everything above 2 accounts for less than 1% of the total bookings. We recoded this feature to be binary, where there is a booking change (1) or no changes (0).



➔ Bookings with **no changes**: **30% canceled**

➔ Bookings with **1 or more changes: 16% canceled**

11) DepositType



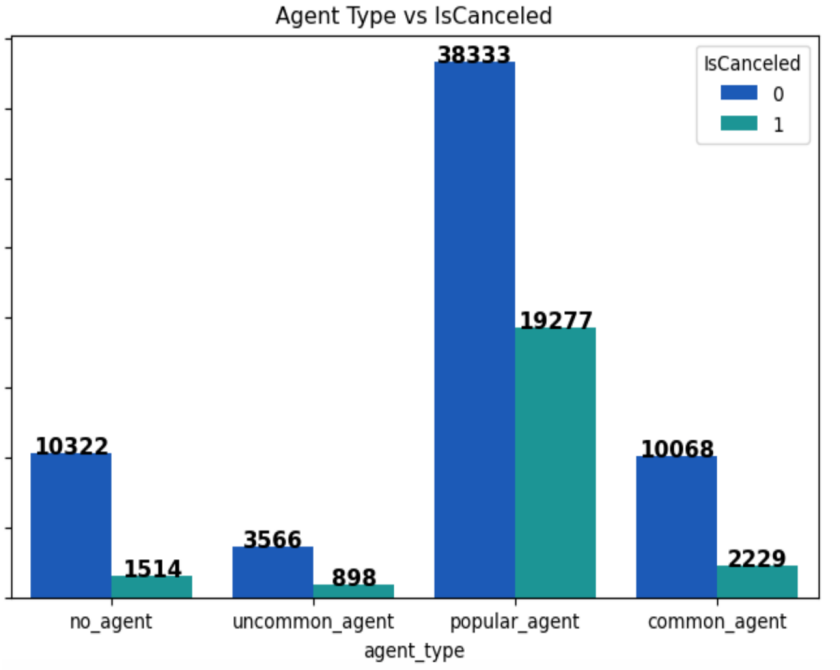
➔ **98.67% of bookings do not have a deposit: 27% canceled**

➔ **1.2% of bookings have a non-refundable reservation: 94.7% canceled**

➔ **Less than 1% of bookings have a refundable deposit: 24.29% canceled**

Only 1.2% of the bookings are in the non-refundable group, but it is counterintuitive that such a high percentage of these bookings are canceled. Upon further inspection, 63% of these bookings are within the 'Groups' market segment. Groups generally have more than 4 people within their party, and as we stated earlier, parties with more people generally cancel more often.

12) agent_type



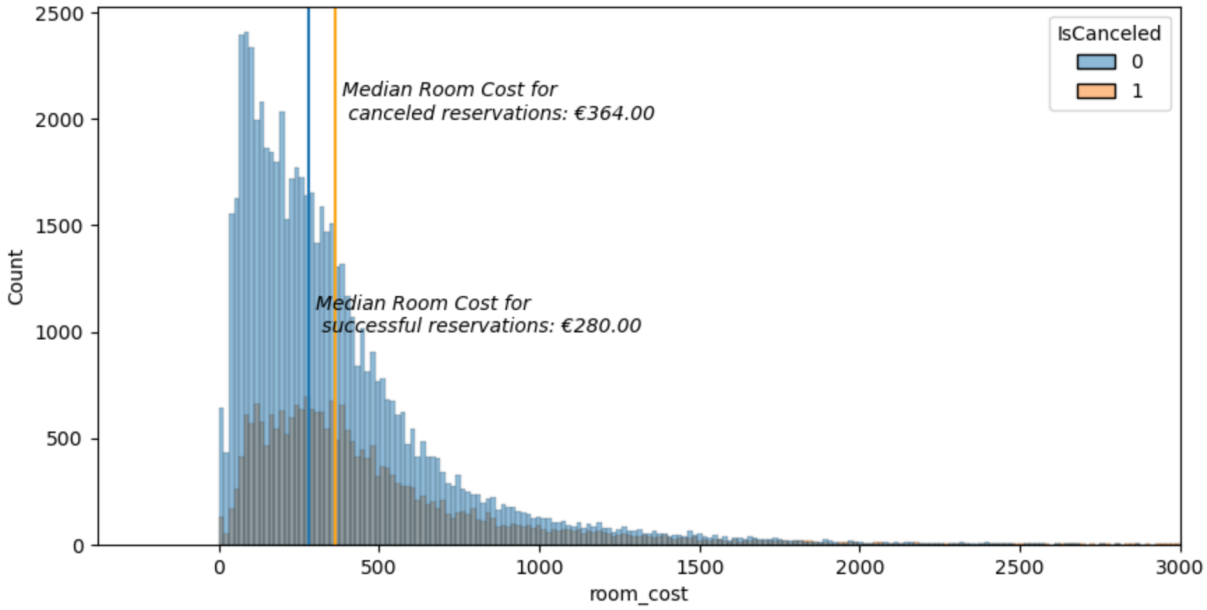
➔ **66.8% of the reservations were made by a popular agent: 33.5% canceled.**

➔ **13.7% of reservations were made without an agent: 12.8% canceled.**

13) wait_list

99% of the bookings are not on a wait list. Of the 834 that are on a wait list, 35% of them canceled.

14) Room Cost



The **median room cost for canceled reservations is $364**, while for **successful reservations it is $280**. This suggests that bookings that cost more tend to cancel more than cheaper bookings, which is to be expected.

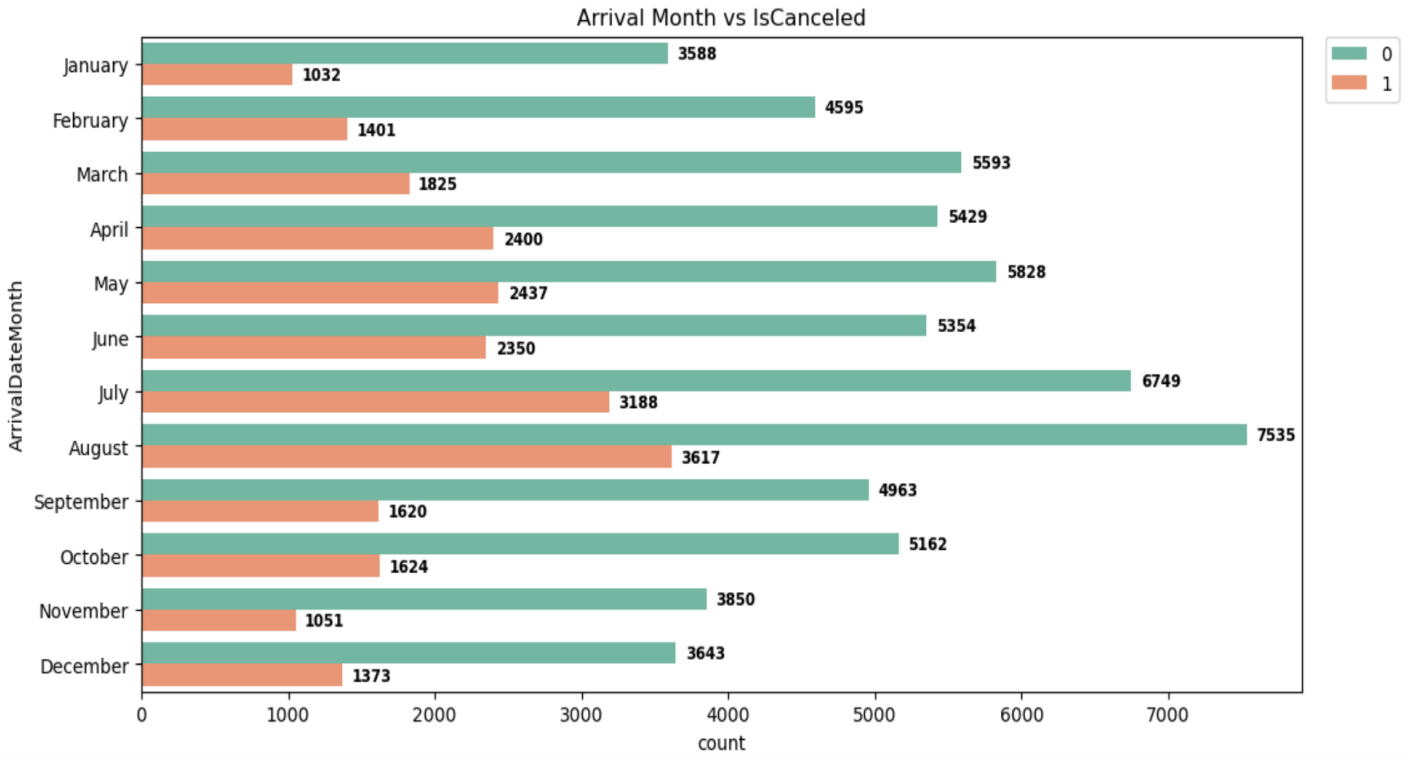
There is approximately €34,446,903 worth of potential revenue if all of the bookings are successful. The cancellations account for about 33% of that, which is a significant loss.

15) RequiredCarSpaces and special_requests

These features were both coded into binary values. **RequiredCarSpaces** indicates if a parking space was requested (1) or not (0). **Special_requests** indicates whether a booking made a special request (1) or not (0).

- ➔ Only 8% of the bookings **required car parking** spaces: **0% canceled**.
- ➔ Approximately 50% of the bookings **made a special request: 22% canceled**.
- ➔ The other 50% **did not make a special request: 34% canceled.**

16) Arrival Month



We can see that the summer months of **July and August** have the most bookings in the dataset, but they also have the most cancellations. **32% of the bookings in those months were canceled.**

Correlation and Associations

Categorical/binary Features

column	Cramer V	Association
MarketSegment	0.221915	strong
res_equals_assign	0.210918	strong
RequiredCarParkingSpaces	0.188054	strong
agent_type	0.185183	strong
DepositType	0.165105	strong
special_requests	0.131184	moderate
CustomerType	0.127644	moderate
BookingChanges	0.125365	moderate
IsRepeatedGuest	0.084595	weak
Continent	0.077996	weak
Hotel	0.071479	weak
Meal	0.057939	weak
is_weekend	0.046879	very weak
is_europe	0.030714	very weak
wait_list	0.016042	very weak

Numerical Features

	IsCanceled
LeadTime	0.183932
cancellation_rate	0.169148
room_cost	0.135016
ADR	0.126152
total_people	0.100367
total_nights	0.081672
PreviousCancellations	0.050797
ArrivalDateDayOfMonth	0.005476
ArrivalDateMonth	0.004739
PreviousBookingsNotCanceled	-0.052452

1. For the categorical/binary features, a Chi-Squared test for association was performed with the following hypotheses:

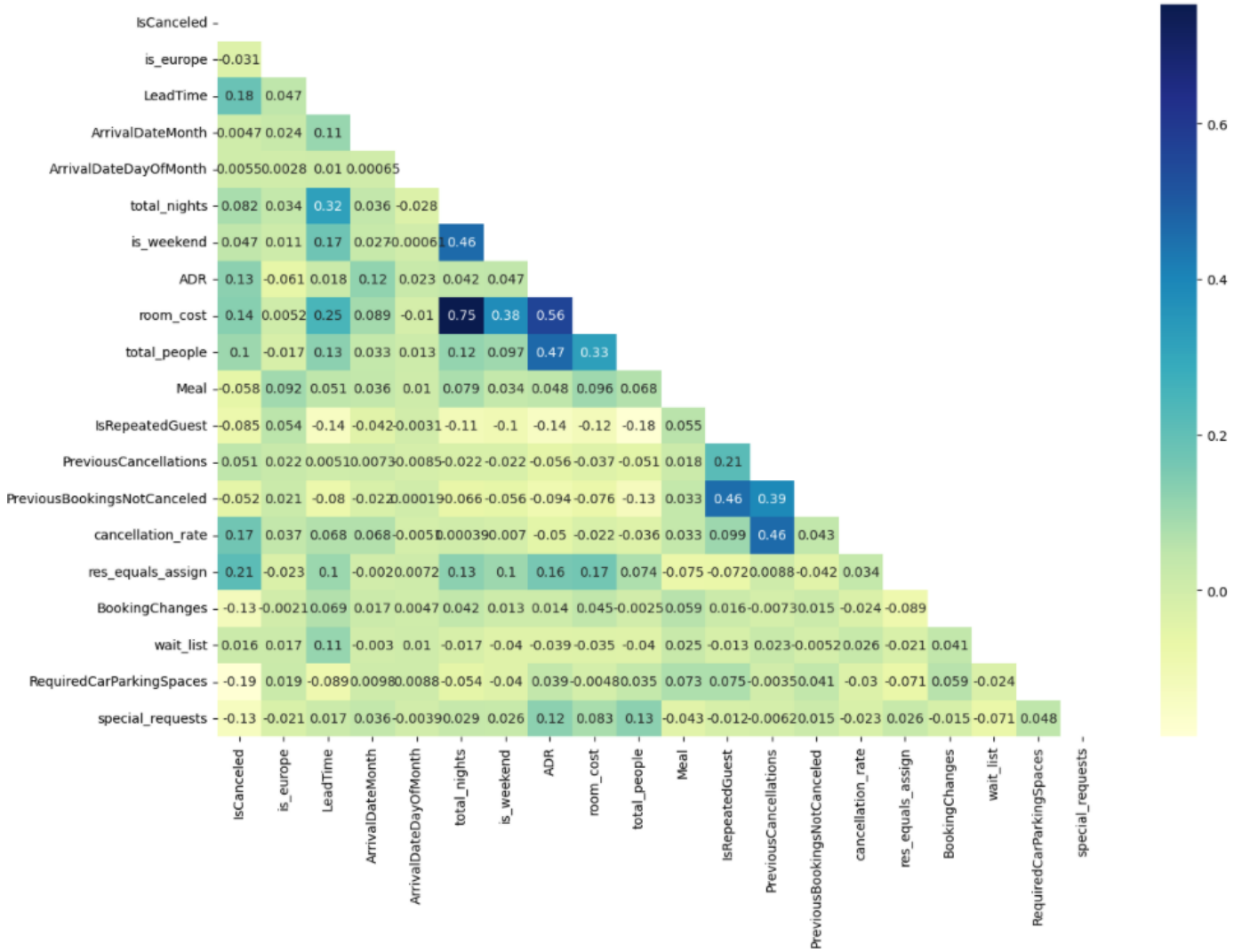
   H_0 = The feature is not associated with the target variable

   H_a = The feature is associated with the target variable

   a. With an alpha of 0.05, the corresponding p-values were all significantly smaller than it. This suggests that we can reject our null hypothesis, however it is more appropriate to utilize the Cramer's V statistic to have a better idea of the strength of these associations.
2. For the numerical features, we used Pearson correlation to check for an association with the target.

Our results from testing for associations suggest that **MarketSegment, res_equals_assign, RequiredCarParkingSpaces, agent_type, deposit_type, LeadTime, cancelation_rate,** and **room_cost** are the most strongly associated with **IsCanceled.**

Correlations between Features:



The correlation heatmap suggests the following strong associations:

- ☐ room_cost ⇔ total_nights, ADR, and total_people
- ☐ Cancelation_rate ⇔ PreviousCancellations
- ☐ IsRepeatedGuest ⇔ PreviousBookingsNotCanceled, PreviousCancellations

To avoid any redundancy or multicollinearity, we will remove **ADR, total_nights, Continent, PreviousBookingsNotCanceled, and PreviousCancellations.**

Modeling

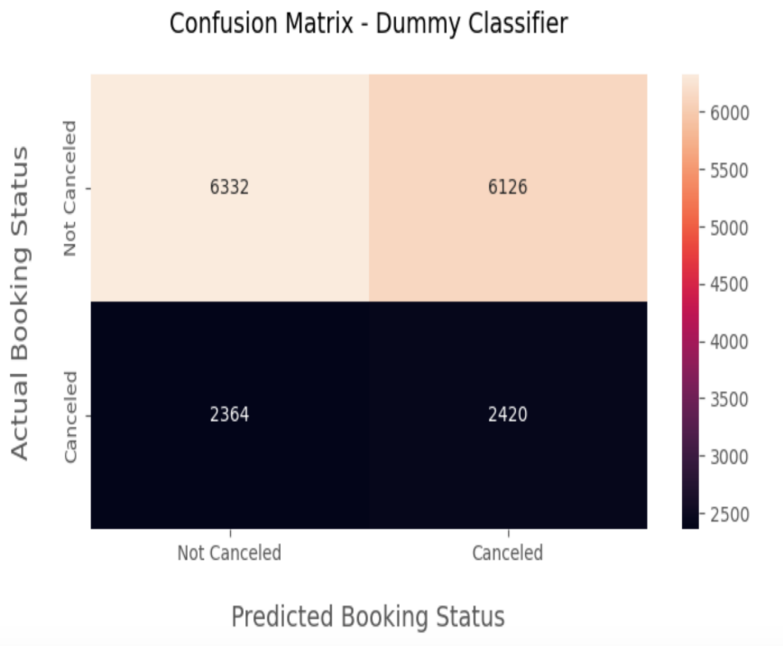
After feature engineering and one-hot encoding our categorical features, we have **86207 rows, and 28 features**. Our data is split into training and test sets, with 20% of the data in the test set.

- Training set: 68965 rows
- Test set: 17242 rows

As mentioned in the EDA section, our target variable 'IsCanceled' has some significant class imbalance. The positive class (canceled) accounts for only 27.7% of the total, so we have to be careful with the metrics we choose to evaluate our models. Pure accuracy will not be appropriate here, so we will be using recall and precision to assess the quality of our models.

I. **Recall** is the true positive rate, or the percentage of actual cancellations that were correctly predicted to cancel. This is our most important metric, as it embodies the goal of this project.
II. **Precision** tells us about the false positive rate. If our model predicts that a booking will cancel, the percentage of those predictions that are actual cancellations will be given by precision.

Baseline: Dummy Classifier

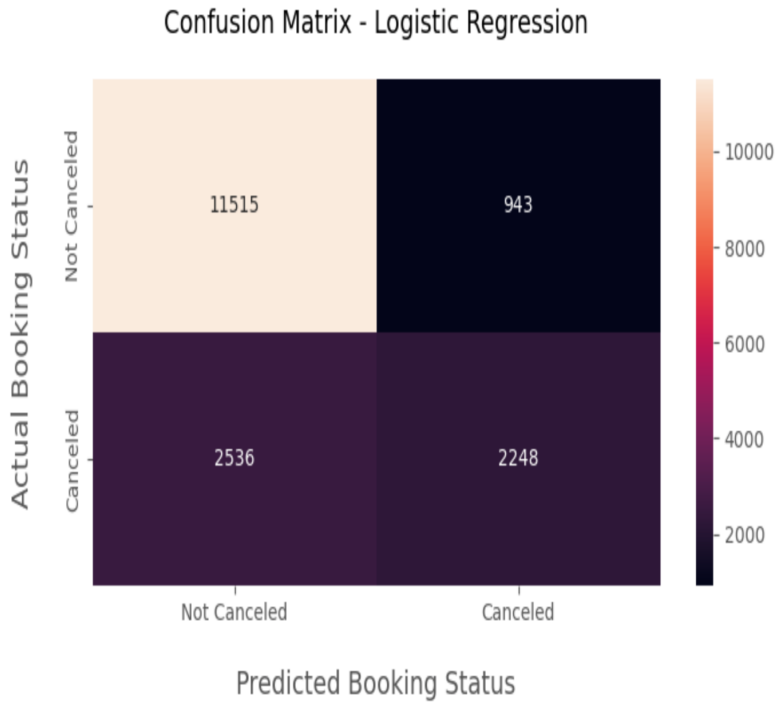


Recall = 50.59%

Precision = 28.32%

Our baseline model performs very poorly, as expected. It is essentially 'guessing' that half of the bookings will cancel. It is able to achieve a 50% true positive rate, but has a very high number of false positives.

Logistic Regression

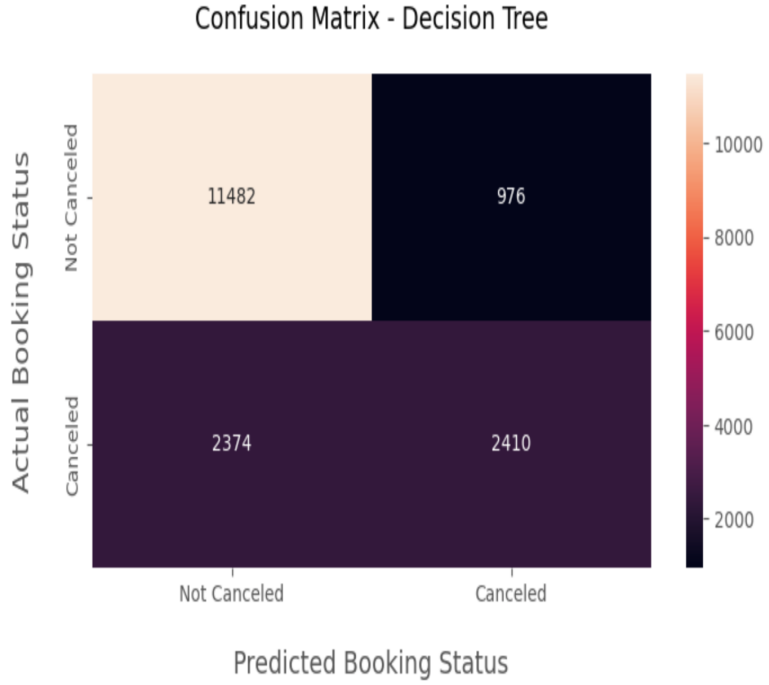


Recall = 46.99%

Precision = 70.45%

Logistic regression improves upon the precision, which results in significantly less false positives. However, the recall is worse than the baseline model.

Decision Tree

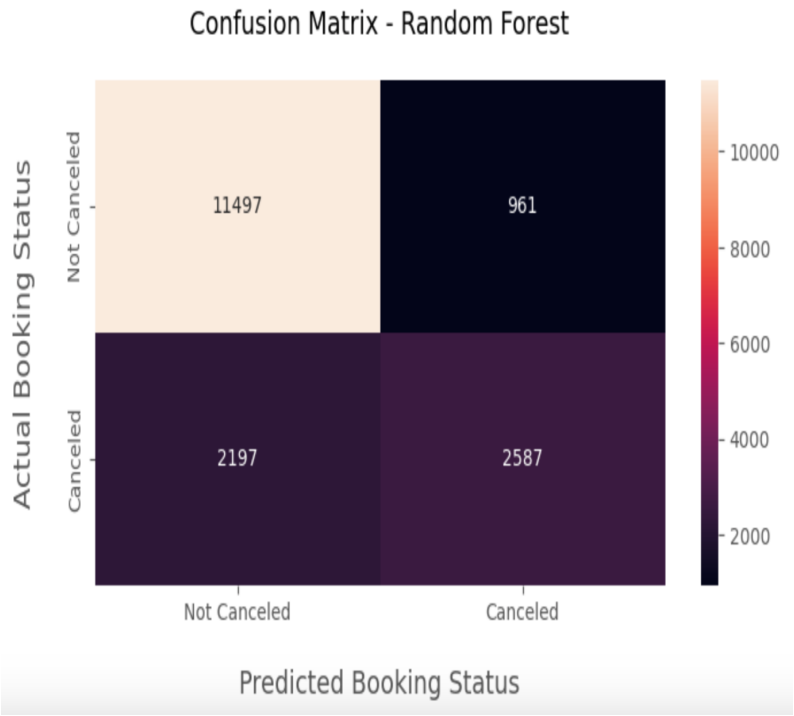


Recall = 50.38%

Precision = 71.18%

The decision tree has a 1% improvement on precision, and the recall is on par with the baseline model. These results are not quite acceptable, as we would like to optimize the recall.

Random Forest

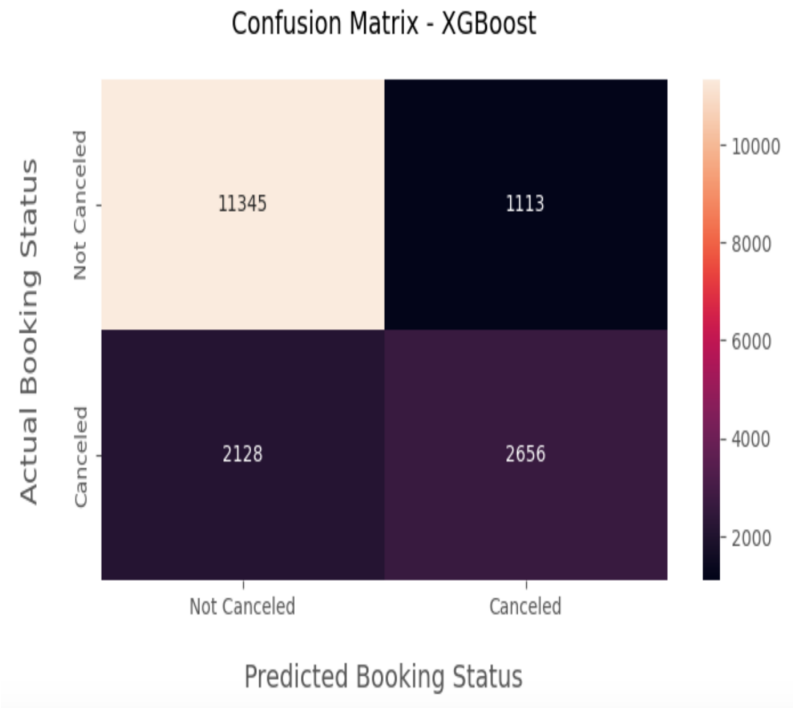


Recall = 54.08%

Precision = 72.29%

Finally, the random forest model improves on the recall of the baseline model by 4%. We will try some boosting methods to try and further optimize our recall.

XGboost

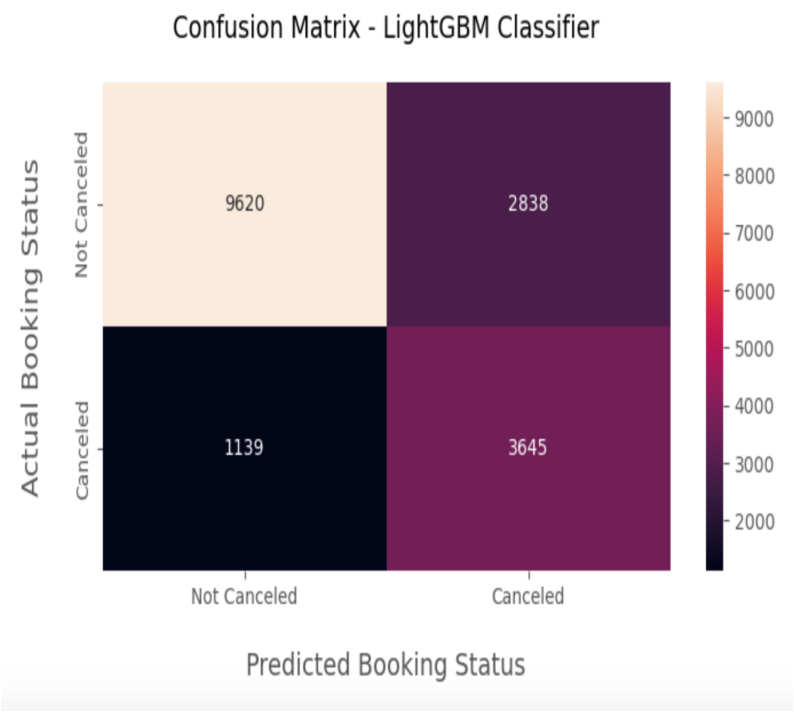


Recall = 55.52%

Precision = 70.47%

XGboost results in a slight 1% improvement in recall, but has a 2% decrease in precision.

LightGBM



Recall = 76.19%

Precision = 56.22%

LightGBM significantly improves on the recall with a 21% increase from XGBoost. Of the 4,784 canceled bookings, the model is correctly identifying 76% of them. However, this model also has a 14% decrease in precision from the XGboost model. These results will be discussed further in the conclusion, but this will be our final model.

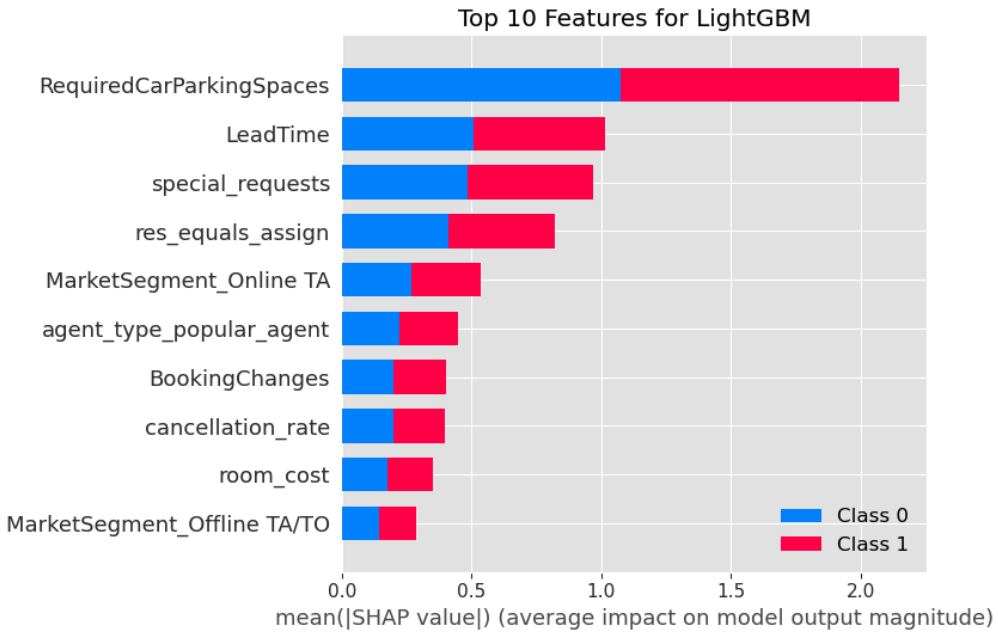
Comparing and Validating Models

	Train Recall	Test Recall	Train Precision	Test Precision	Train Accuracy	Test Accuracy	Train AUC	Test AUC
Dummy Classifier	0.505906	0.505853	0.280166	0.283173	0.502284	0.507598	0.503399	0.507060
Logistic Regression	0.486987	0.469900	0.712603	0.704481	0.803176	0.798225	0.705786	0.697103
Decision Tree	0.525870	0.503763	0.725555	0.711754	0.813268	0.805707	0.724746	0.712710
Random Forest	0.822828	0.540761	0.950094	0.729143	0.938853	0.816843	0.903116	0.731811
XGBoost	0.655900	0.555184	0.806866	0.704696	0.860973	0.812029	0.797808	0.732922
LightGBM	0.818856	0.761915	0.603126	0.562240	0.800247	0.769342	0.805979	0.767055

The models have been applied to both the training and test sets to check for overfitting. Logistic regression and the decision tree classifiers both have a low variance, and thus do not have an overfitting issue. The random forest has a significantly higher variance, and while not as severe, XGBoost also has a high variance. Of the high performing models, LightGBM has the lowest variance with only a 5% difference in recall between train and test sets. To further validate these results, 5-fold cross validation was performed on LightGBM and a mean recall of 0.76 was achieved, suggesting that our model does not have an overfitting issue.

The overall accuracy was included in the table to showcase the issue with using it as a metric when class imbalance is present. Other than the baseline, it has the lowest test accuracy. This is extremely misleading, as it is the model that performs the best at predicting true positives. A more appropriate metric is the AUC, or the area under the ROC curve. The ROC curve describes the relationship between the true positive rate and false positive rate, and thus optimizing the area under the curve results in a higher performing model.

Feature Importance



The 10 most important features used by the LightGBM model are displayed in the figure above, and these results seem to closely align with our observations from the EDA section:

1. Required car parking spaces being the most important makes sense, as we saw the bookings that requested a space never canceled.
2. For lead time we saw a significant difference in the median between the two groups, concluding that reservations made farther in advance were more likely to cancel.
3. We found that bookings with special requests were less likely to cancel.
4. Customers who did not receive the same room type that they booked canceled less often.
5. Customers from the Online TA market segment canceled more frequently.
6. Bookings made by a popular agent canceled more frequently.
7. Changes to the booking resulted in less cancellations
8. Customers that previously canceled also had more current cancellations.
9. Higher room cost results in more cancellations
10. The offline TA/TO market segment has significantly less cancellations.

Conclusions

The LightGB model overall had the most acceptable results for the specific business value that we are trying to provide. Of the **4,784 canceled bookings** in our test set, the model is **correctly identifying 76% of them**. However, this model also has a significant decrease in precision. This is not necessarily an issue, as the precision describes the bookings that were predicted to cancel but actually did NOT cancel.

To reiterate the goal of this project, we are looking to identify bookings that are likely to cancel in order to attempt and retain the bookings. If a customer wasn't going to cancel anyway then it doesn't necessarily hurt to misclassify them. Of those **12,458 successful bookings** in the test set, only **22.7% are misclassified** as being canceled.

It is important to note that depending on the strategy used to retain the bookings, it could have a negative impact on profit. For example, if the hotel offers complimentary nights to every booking predicted to be at risk of canceling then this could be very costly. However, we do not know this for sure. Financial data for these hotels is not readily available, and so we are unable to explore what the actual costs would be. One way the business can deal with this is to make decisions not based on the model classifications, but on the corresponding probabilities.

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

The table above shows a sample of 5 bookings. Row 1 was a successful booking, but was predicted to be canceled. The model made that decision with only a 58.7% probability. Row 2 on the other hand was a canceled booking that was correctly predicted to be canceled with 88% probability. A probability threshold may be needed when making the final decision on which bookings should be targeted to retain.

Ideas for Implementation:

I. Bookings predicted to cancel with **at least 70% probability** will receive:
   A. An email
   B. A phone call
   C. Complementary nights, meals, other services (if costs allow)

II. Bookings predicted to cancel with **less than a 70% probability** will receive:
   A. An email
   B. A phone call

Further Work

Without financial data related to the hotel revenue and profit, there is no way of knowing how many incentives the hotel can realistically offer. Of the 6,483 bookings predicted by the model to cancel, how many complementary rooms or meals can be given without hurting the profits? With financial data this can be explored further, and a more accurate business decision can be made.

In terms of improving the model, one feature that is currently unknown to us is weather information. It is intuitive to expect that many cancellations are weather related, and so having weather forecast data may be helpful. For instance, if a storm is expected over the North Atlantic Ocean, then customers traveling from North America will likely cancel.