

FutureTale Hotel Reservation Case Study

Case Study Overview

FutureTale Hotel speaks dynamic modernity. The Chinese Restaurant, Japanese Gourmet Restaurant, Lobby Lounge & Bars, and Grand Ballroom, as well as the guest rooms and suites, meet the most exacting comfort and service standards.

FutureTale hotel has noticed inconsistencies in their returns from 2017 to 2018. Being a modern relaxation center with a booking platform, A significant number of hotel reservations are called-off due to cancellations or no-shows. The typical reasons for cancellations include change of plans, scheduling conflicts, etc. This is often made easier by the option to do so free of charge or preferably at a low cost which is beneficial to hotel guests, but it is a less desirable and possibly revenue-diminishing factor for hotels to deal with.

You have been employed as a Data Scientist to explore the data and provide some insights and recommendations

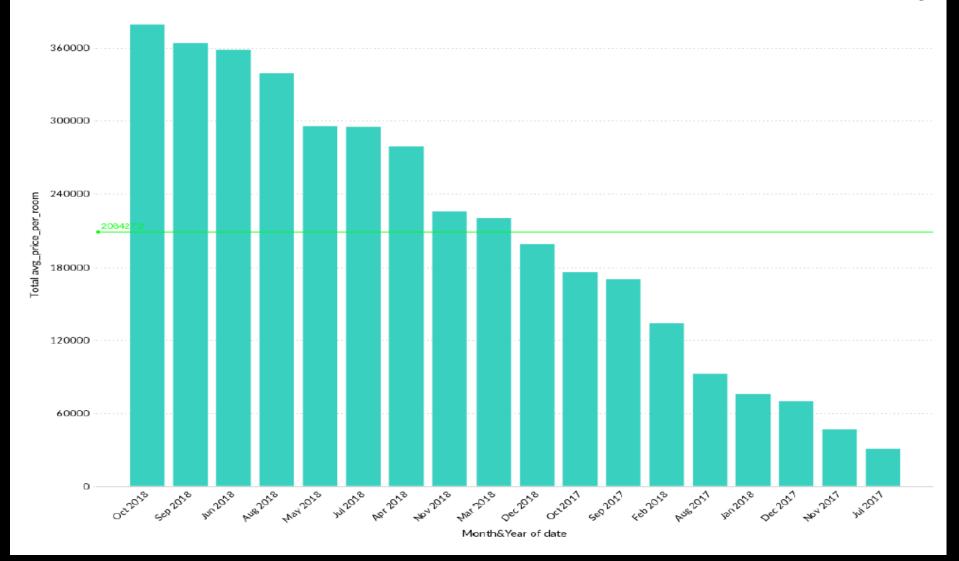
DATA DICTIONARY

- 1. **Booking_ID**: unique identifier of each booking
- 2. no of adults: Number of adults
- 3. no_of_children: Number of Children
- **4. no_of_weekend_nights**: Number of weekend nights (Saturday or Sunday) the guest stayed or booked to stay at the hotel
- 5. no_of_week_nights: Number of weeknights (Monday to Friday) the guest stayed or booked to stay at the hotel
- **6. type_of_meal_plan**: Type of meal plan booked by the customer:
- 7. required_car_parking_space: Does the customer require a car parking space? (0 No, 1- Yes)
- 8. room_type_reserved: Type of room reserved by the customer. The values are ciphered (encoded) by INN Hotels.
- **9. lead_time**: Number of days between the date of booking and the arrival date
- 10. arrival_year: Year of arrival date
- 11. arrival month: Month of arrival date
- 12. arrival date: Date of the month
- 13. market_segment_type: Market segment designation.
- **14. repeated_guest**: Is the customer a repeated guest? (0 No, 1- Yes)
- **15. no_of_previous_cancellations**: Number of previous bookings that were canceled by the customer prior to the current booking
- **16. no_of_previous_bookings_not_canceled**: Number of previous bookings not canceled by the customer prior to the current booking
- 17. avg_price_per_room: Average price per day of the reservation; prices of the rooms are dynamic. (in euros)
- **18. no_of_special_requests**: Total number of special requests made by the customer (e.g. high floor, view from the room, etc)
- **19. booking_status**: Flag indicating if the booking was canceled or not.

avg_price_per_room Across Months

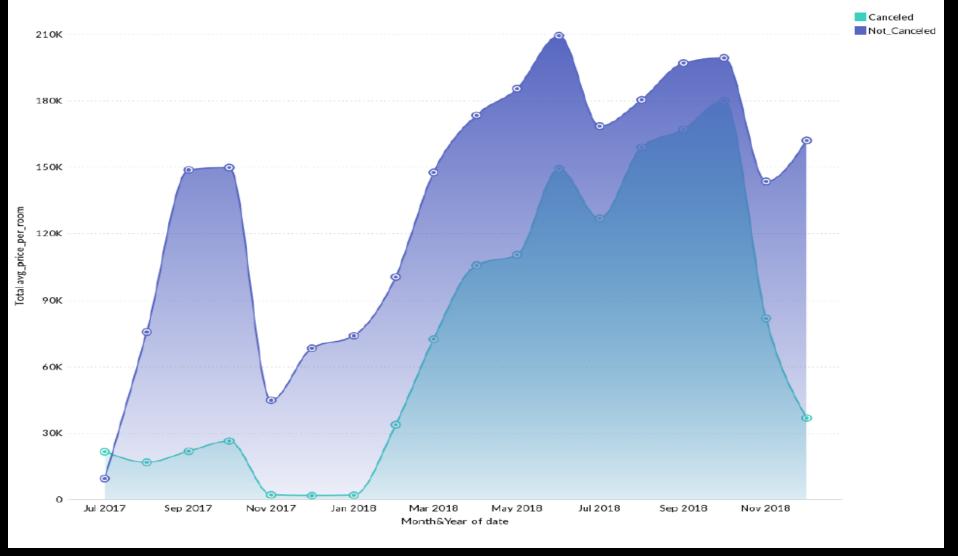
avg_price_per_room across Months (based on date)

Threshold: — Average



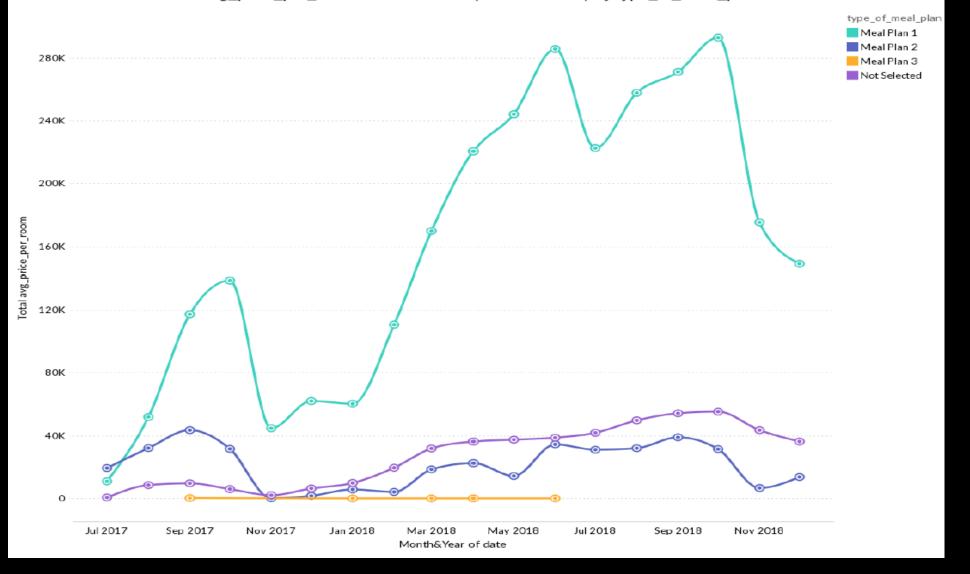
avg_price_per_room Across Months by booking_status

avg_price_per_room across Months (based on date) by booking_status



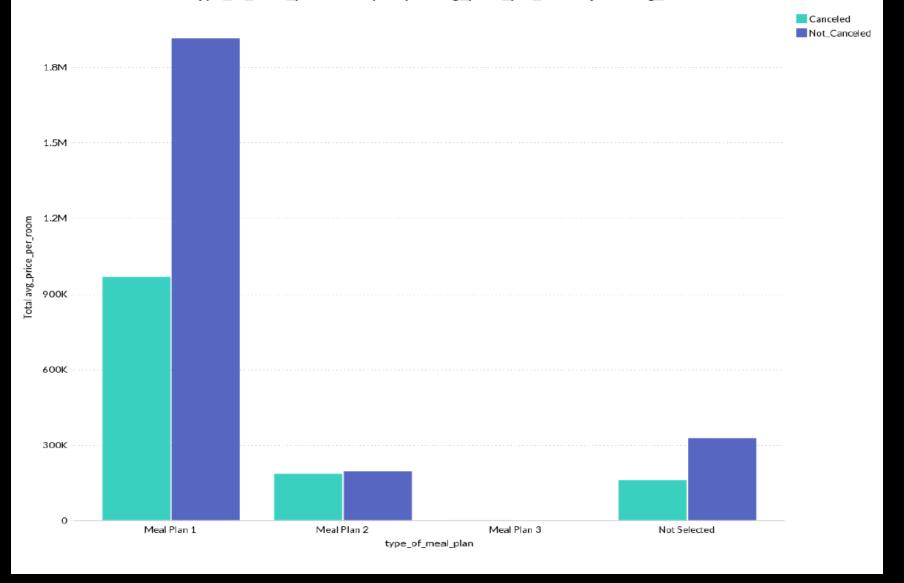
avg_price_per_room Across Months by type_of_meal_plan

avg_price_per_room across Months (based on date) by type_of_meal_plan



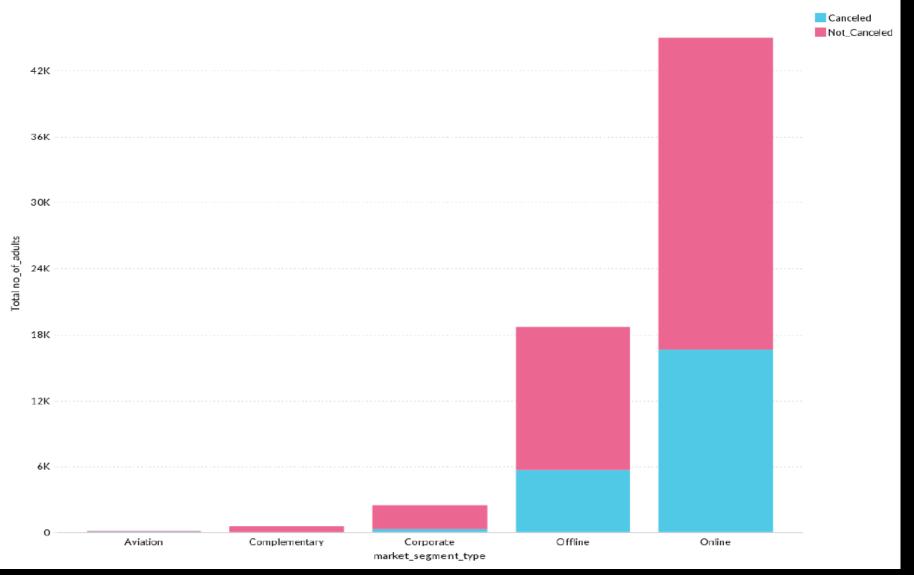
type_of_meal_plan-wise avg_price_per_room by booking_status

type_of_meal_plan-wise split up of avg_price_per_room by booking_status



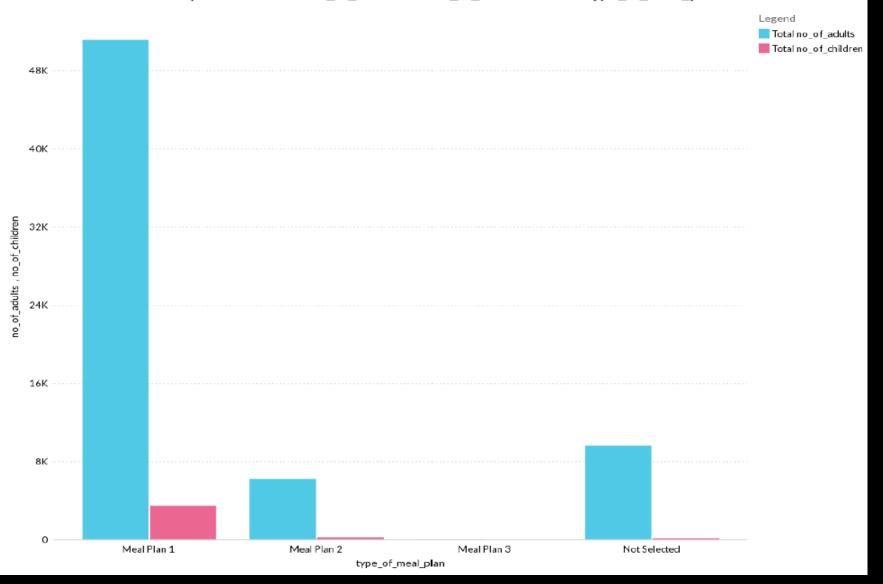
market_segment_type-wise no_of_adults by booking_status

market_segment_type-wise split up of no_of_adults by booking_status



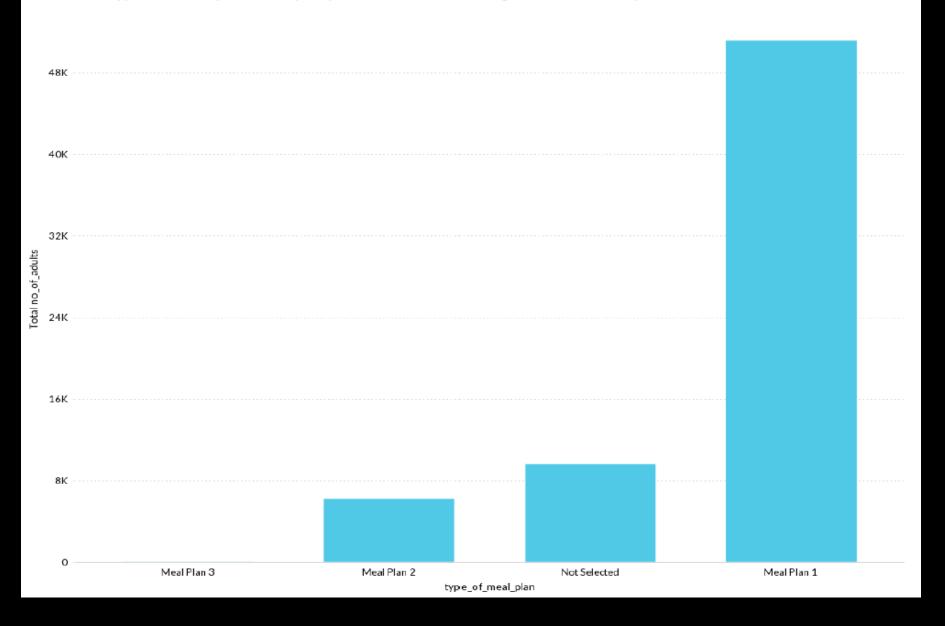
no_of_adults vs no_of_children by type_of_meal_plan

Comparison between no_of_adults and no_of_children across type_of_meal_plan



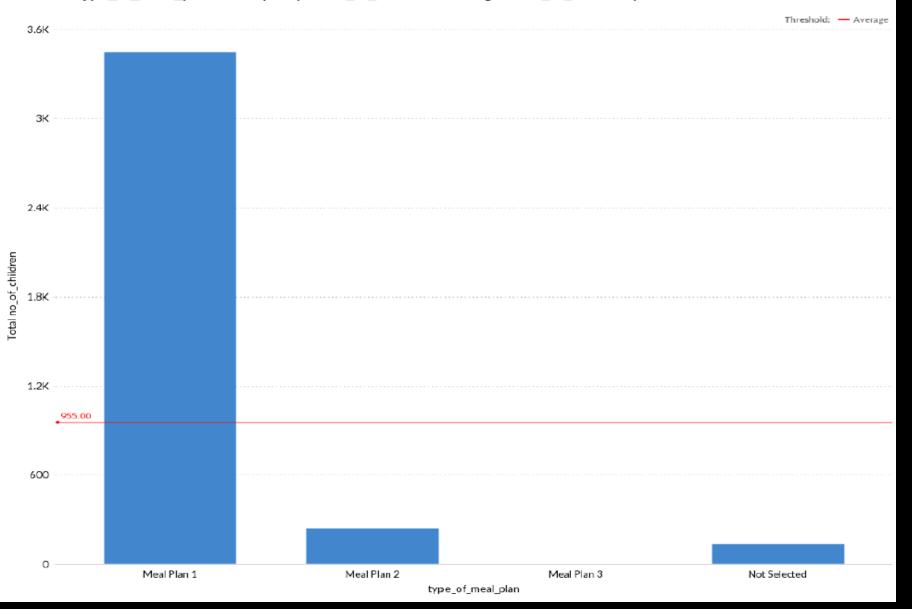
type_of_meal_plan-wise no_of_adults

type_of_meal_plan-wise split up of no_of_adults. Average of no_of_adults plotted as Threshold value



type_of_meal_plan-wise no_of_children

type_of_meal_plan-wise split up of no_of_children. Average of no_of_children plotted as Threshold value



Recommendations

1. High Cancellation Segments:

Introductions of stricter cancellation policies or non-refundable rates for segments (e.g. "Meal_plan 2" in the Meal_plan segment and room_type_6 in the Room_type_reserved segment have high cancellation rates.

2. Lead Time Management:

Implement dynamic pricing strategies where the price increases as the lead time increases to incentivize commitment.

3. Special Requests and Flexibility (High special requests between September – October)

Guests with more special requests might be less likely to cancel. It is recommended that offering personalized services and incentives for guests who make special requests may reduce cancellation rates.

4. Optimizing market_segment:

Some market_segment_types have high cancellation behaviors. (e.g., online, offline & aviation channels)

Optimize these booking channels by offering promotions or stricter policies on channels with higher cancellation rates.

5. Seasonal Patterns:

Seasonal trends in cancellations (e.g., Higher cancellations between February - November).

Recommendation: Implement targeted marketing campaigns during historically lower cancellations and adjust staffing and inventory accordingly.