

# **Navigating the World of Hospitality: A Business Analytics Journey**

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## **1 Introduction**

In the Expanding landscape of the service industry and Hotel management, Data analysis serves as a light, illuminating patterns, trends, opportunities, and customer preferences to generate insightful and useful information. Our journey into the Hotel Dataset begins by meticulously preparing the data of 119,390 entries for further analysis. With the help of interactive dashboards and future predictive models, this report aims to provide value to the management team and help them make more informed decisions.

## **2 Methodology/ Data Preparation**

We initiated our data analysis by cleaning the dataset and making it compatible with SAS by transforming the three-letter country codes into a two-letter country code. This cleaned data was then imported into SAS Viya and Excel where we converted arrival\_date\_day\_of\_month, arrival\_date\_week\_number, arrival\_date\_year, is\_repeated\_guests, and is\_canceled to categorical variables. We then proceeded to find the outliers and remove them by using the following code on SAS ( 'adr'n <= 198 ) AND ( 'adr'n >= 0 ) AND ( 'lead\_time'n <= 354 ). Lastly, in collaboration with our international member from SCMS and her Power BI skills, we created interactive dashboards on SAS and Power BI to generate some business insights.

## **3 Descriptive Statistics**

Our descriptive statistics were done by using Python, employing the “.describe()” to generate some descriptive statistics. In the process, we found out that the dataset consists of 119,390 entries in total consisting of categorical, numerical, and dummy variables.

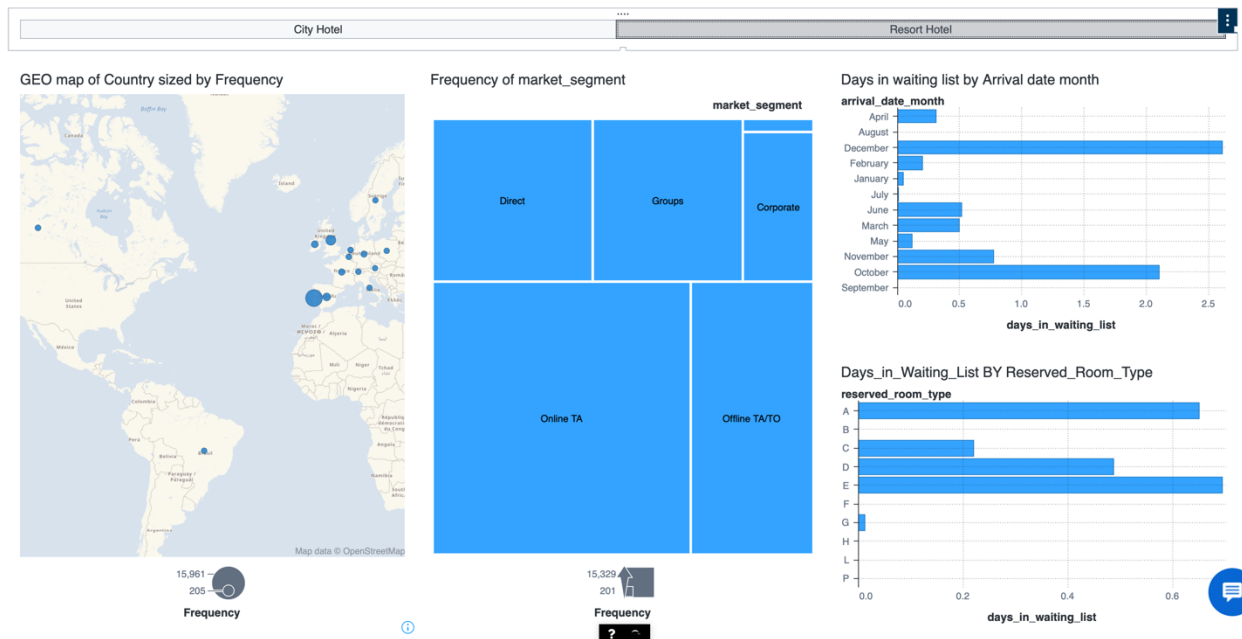
We then identified our key variables to be the Average Daily Rate (ADR). Lastly, we calculated the count, mean, standard deviation, minimum, and maximum values through Python. The mean ADR was observed to be 101.8 and the mean Lead Time was observed to be 104 days.

## 4 Dashboards

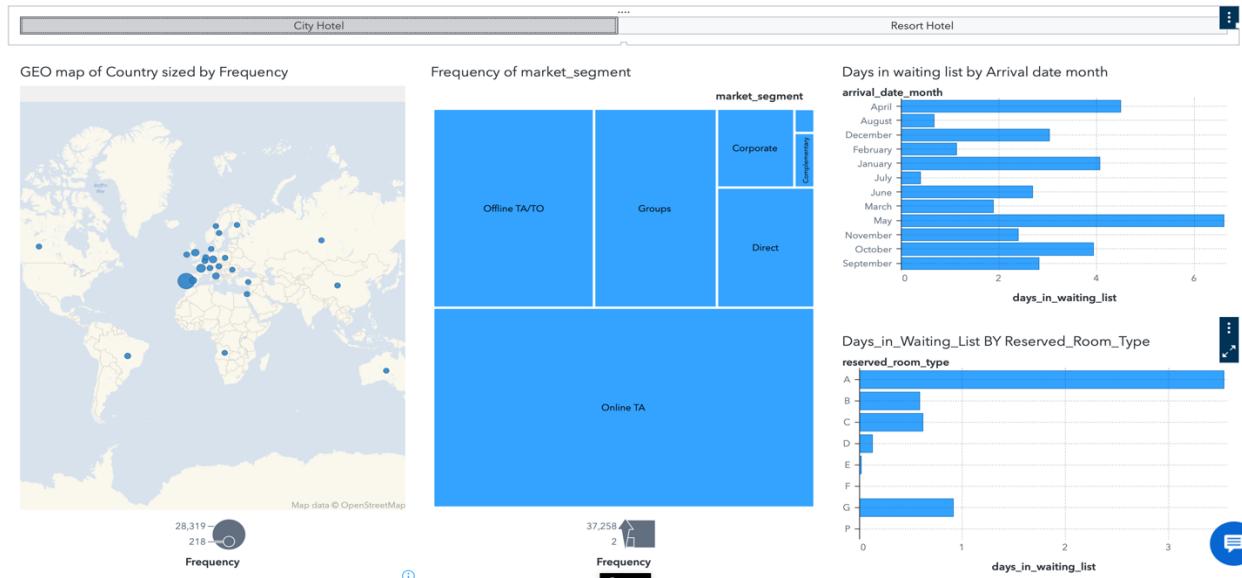
### 4.1 Product Analysis Dashboard

We started off by creating an interactive Dashboard that provides us with compelling insights into the distribution of different hotel types (City and Resort) based on their frequency. The dashboard also provides a detailed analysis of the market segment, days on the waiting list by arrival month, and room type.

#### Resort Hotel



#### City Hotel



The Geo Map visually represents the geographical distribution of city and resort hotels in different countries as well as provides the total number of bookings for each hotel type. The TreeMap enables us to interactively explore the waiting times of customers based on different market segments. Lastly Both the bar graphs give insight into the most popular month and room type based on different market segments, hotel types, and countries.

#### 4.1.1 Business Insights

##### *Business Insight 1: Global Distribution Insights*

Upon observing the Geo Map, it was found that the company's Resort Hotels were more European based whereas its city hotels were more worldwide with branches in Angola, Canada, Brazil Russia, China, and Australia. It was also observed that Portugal was the busiest city in terms of booking frequencies.

##### *Business Insight 2: Peak Demand Month Analysis*

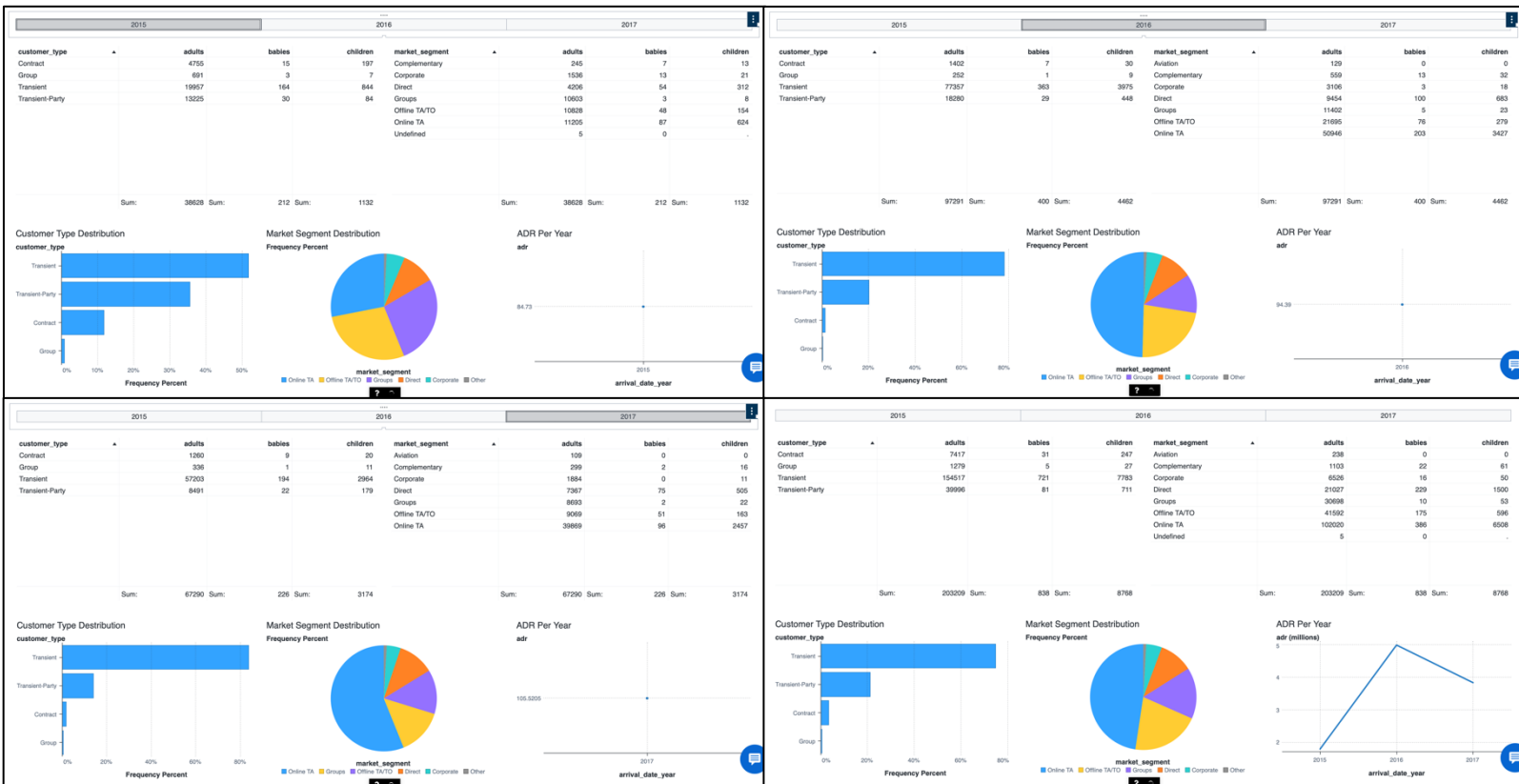
Upon our analysis, we found that April, May, and January had the highest number of days on the waiting list for City Hotels. Whereas in terms of Resort Hotels, October and December resulted to be the busiest months. This lets us know the popularity among guests during these months.

##### *Business Insight 3: Peak Demand Room Type Analysis*

After analyzing the Room type graph, it was observed that Room Type A was the most popular among City Hotels. Whereas Room Type E was the most popular room among Resort Hotels

## 4.2 Customer Analysis Dashboard

The Customer Analysis Dashboard provides a comprehensive and detailed analysis of hotel bookings by focusing on the distribution of guests across different customer types and market segmentations over the years. Additionally, it visually represents the distribution of Customer Types, Market Segments, and ADR over the years with the help of a Bar, Pie, and Line graph.



The dashboard is divided into 2 sections, *Section 1*: Provides us with details on the total count of adults, children, and babies categorized by different market segments and customer types. *Section 2*: A Bar graph is used to analyze the annual distribution of various customer types over the years allowing us to identify valuable information and insights. A pie chart was used to analyze the percentage of customers from each market segment allowing us to deeply understand the market dynamic. Lastly, by using a line graph, we analyzed the Average daily rate of the rooms over the years. The data for different years could be toggled by using the button bar.

### 4.2.1 Business Insights

#### *Business insight 4: Raise in Transient Customers*

An upward trajectory is observed in the number of transient customers over the years. Notably, we observed a substantial increase of 26.49% in transient customers between 2015 and 2016 and an increase of 5.39% between 2016 and 2017. This suggests that there is a change in customer preference as they prefer a more flexible and personal reservation option.

#### *Business Insight 5: The Increasing Popularity of Online Booking*

From the Dashboard, we also noticed an increase in the Online booking market segment over the years. A significant increase of 21.5% increase in online booking was observed between 2015 and 2016 and another 6.51% increase was observed between 2016 and 2017. Indicating the shift in customer preferences to online reservations that are more convenient.

#### *Business Insight 6: Declining Rate of Contract and Group Bookings*

Although we noticed a rise in transient customers and online booking types, we also observed a noticeable reduction in the contract and group booking types. It was observed that contract booking type decreased from 11.83% in 2015 to 1.77% in 2017. Similarly, group customer types decreased from 0.90% in 2015 to 0.56% in 2017. This could result as catastrophic for the hotel's financial performance.

#### *Business Insight 7: Changes In ADR*

From the ADR line graph, it was observed that the Average Daily Rate significantly increased from 2015 to 2016 but saw a slight decrease in 2017. This further highlights the flaw we witnessed in *Insight 6*.

## 4.3 Customer Behavior Dashboard

This Dynamic Dashboard offers a comprehensive visualization of customer behavior, with the help of a Butterfly Graph, TreeMap, Correlation Matrix/Heat Map, and a Bar Graph, we focused on different market segments to provide valuable insights into customer booking, cancellation, changing patterns, and customer retention over various years.



The Butterfly Graph and TreeMap visualize and depict the sum of bookings that were previously canceled or not canceled by each customer type. This provides us with valuable insights to understand the cancellation patterns of the customers. With the help of a Heat Map, we made a correlation matrix that depicts the correlation between customer type and booking changes. This helps us to gain insights into which customer types are more likely to change their bookings and identify potential patterns and trends. The Bar Graph visualizes customer retention over the years enabling us to identify which market segments have seen an increase or decrease in their customer retention.

#### 4.3.1 Business Insights

##### *Business Insight 8: Cancellation Risk Analysis*

The Butterfly and TreeMap drew our attention to the fact that the “Contract” customer type exhibited the highest frequency of previous cancellations (especially contract customer types under the “Group” market segment) followed by Transient Party and Transient. Providing us the insight into which customer types are more likely to cancel their reservations. This allows the management team to take measures to reduce the cancellation risks for the company.

##### *Business Insight 9: Booking Change Patterns*

From the Correlation Matrix/ Heat Map, it was observed that the Online TA - Transient Party customer types were more likely to change their bookings followed by Direct-Transient and Group-Transient Parties.

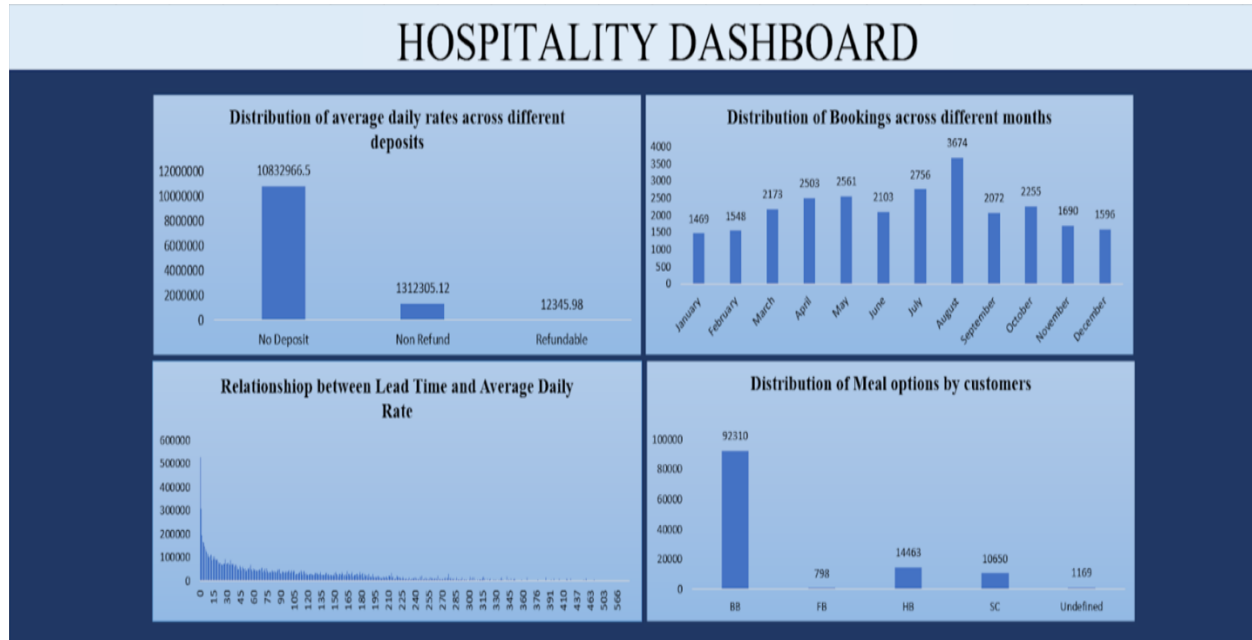
##### *Business Insight 10: Customer Retention Insights*

From the customer retention bar graph, it was observed that the ‘corporate’ market segment had the highest percentage – 27.83% of repeat customers followed by Direct – 6.65%, Offline TA – 1.64%, Groups – 1.53%, and lastly Online TA with the lowest customer retention percentage of 1.09%



## 4.4 Hospitality Dashboard

The Hospitality dashboard assesses the revenue and overall customer satisfaction by leveraging Customer Data. The dashboard consists of multiple bar graphs that give us insightful information.



This dashboard analyses the distribution of the Average Daily Rate (ADR) across different deposit types to visualize the most preferable one. Second, we analyzed the popularity of the months in terms of total bookings, and the popularity of meal type, and lastly, we analyzed the correlation between Lead time and ADR.

### 4.4.1 Business Insights

#### *Business Insight 11: ADR-Deposit Type Analysis*

After analyzing the ADR-Deposit\_type graph, we found that the “no deposit” type had the highest ADR followed by non-refundable and refundable booking. Through these insights, we concluded that our guests are willing to pay a premium amount if it means that it is convenient for them, and they do not have to go through the hassle of depositing money.

#### *Business Insight 12: Peak Season Analysis*

June and September are the most popular months which align with the vacation period for educational institutions.

#### *Business Insight 13: Lead Time and Average Daily Rate*

We analyzed an inverse relationship between lead time and average daily rate showing us that guests who book their stays in advance tend to pay less money.

#### *Business 14: Dining Preferences*

Breakfast was the most popular meal option among guests followed by Half Board (consisting of 2 meals per day, usually breakfast and dinner) and Self Catering.

## **5 Recommendation**

### Optimizing Inventory

It was found that Room Type A had the most popularity among the guests. Thus, the hotel can work towards allocating a higher proportion of Room Type A in their inventory to accommodate the high demand.

### Boosting Off-Season Occupancy

The hotel can encourage off-peak stays by offering enticing incentives such as discounts, complimentary services, and Loyalty programs. By doing this, the company will not only bring in customers during off seasons but also develop customer loyalty.

### Addressing the Increase in Transient Customers

The drastic rise in transient customers shines a light on the importance of offering quick and responsive booking solutions. The hotel can also investigate enhancing the agility of the booking process to cater to the rising demand.

### Enhancing the Guests' Experience

With the rise in preferences in online booking types, it has become evident that customers prefer real-time, quick, and on-the-go booking experiences. Highlighting the importance of developing a robust, secure, and easy-to-use online platform/ website. They should also continuously innovate their digital guest experience and make sure that their online booking process remains intuitive, streamlined, and responsive.

### Bringing back lost Customer Types

The yearly decrease in contract and group booking types is unfavorable for the hotel as it affects its profit. Thus, the hotel should tailor their marketing strategies to target these customers. They can also look to partnering with holiday/ booking agencies to increase engagement with these demographics.

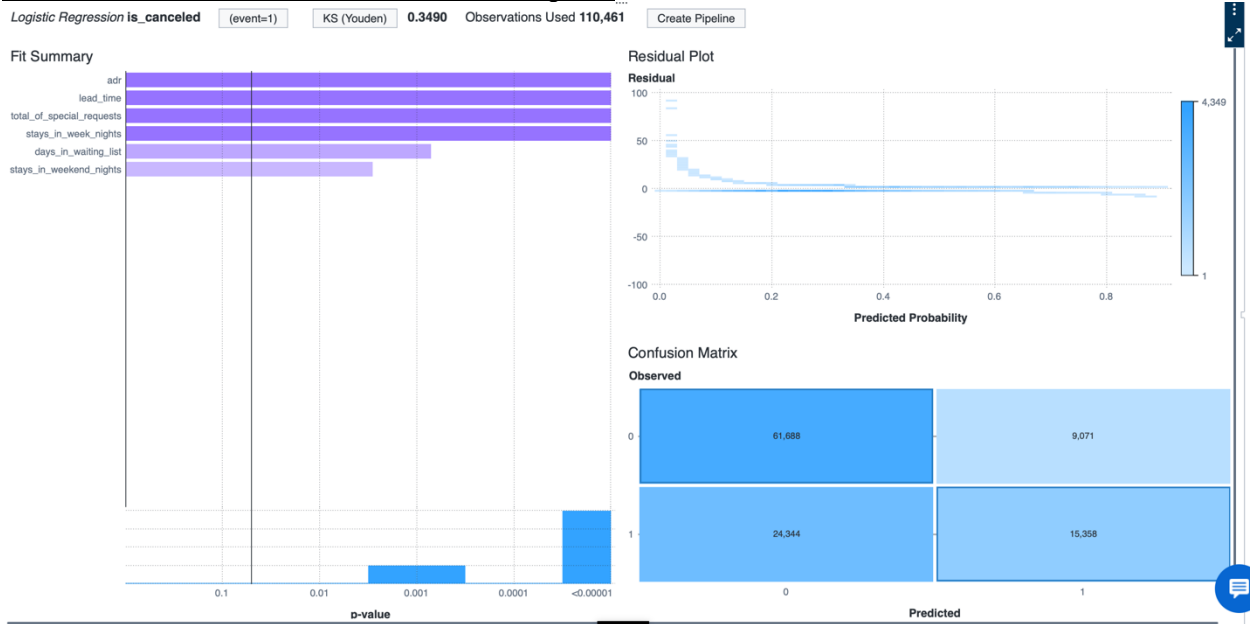
Implementing a Competitive and Dynamic Pricing Model

The decreasing ADR from 2016 to 2017 raises a concern for the financial performance of the hotel. To counteract this, the hotel can look into implementing a competitive and dynamic pricing strategy into its business model. They can also implement an AI-powered Revenue management model that gathers historical booking data, Competitor's pricing, and the demand in the market to adjust their prices in real-time. Forecasting the time periods with the highest cancellation rates can help hotels prepare for cancellation risks and take appropriate measures to mitigate them.

Elevate the Quality of service provided.

Training the hotel staff to adapt to booking changes equips them to navigate effectively and efficiently through booking changes and modifications. By doing this, employees would be able to ensure that the guests have a positive and smooth stay at their hotel, in turn building brand reputation and customer loyalty. From our analysis, we noticed that Transient Customers with the Online booking type had the most changes in their reservations. Thus, by using similar forecasting methods, the hotel can predict if customers might make changes in their bookings and be better prepared for them. These strategic implementations not only enhance operational efficiency but also allow the hotel to tailor its services to the needs of its clients.

6 Future Direction for the Project



With the help of additional forecasting data such as revenue, Historical booking data, Market demand, etc. This project can be taken further by implementing predictive models such as

regression, forecasting, forest models, gradient boosting, etc. to generate deeper insights such as predicting trends, Demand forecasting, Revenue forecasting, etc. These insights will then help the management team of the hotel to make accurate and informed decisions.

An example of this can be seen above where we analyzed the factors that affect the cancellation rate by keeping `is_canceled` as the dependent variable and our independent variables were `ADR`, `lead_time`, `total_of_special_requests`, `stays_in_weekend_nights`, `stays_in_week_nights`, and `days_in_waiting_list`. It was found that `ADR`, lead time, number of special requests, and stays on weeknights were variables that significantly affected the cancellation rate whereas days on the waiting list and stays on weekend nights weren't as significant as compared to others. Although these insights are useful, we can see that the R-square of the model is low (0.3490), meaning the model is not completely accurate, this could happen due to various reasons such as inadequate predictive power, poor model fit, etc. Thus, in the future, this can be worked upon to generate better and more accurate insights.

## **7 Reflective Essay**

### **7.1 My expectations from this project**

Embarking on this Business Analytics project, I had high expectations in terms of generating valuable and useful business insights that would help the company to improve, enhance, and streamline its financial performance and service offerings. I also expected to apply my knowledge of SAS Viya and Python to aid me in this journey. Lastly, I wanted to generate a good business analytics report as it would help me perfect my report-writing skills which will be a valuable tool for my future assignments as well as my work life.

### **7.2 The Problems We Faced and how we solved them.**

Initially, when we decided to create a geo map, we were hindered by a massive roadblock as SAS only accepted a 2-letter country code. Thus, it became a challenge for us to find a way to convert the codes into either 2-letters or country names. Eventually, while searching for solutions for this problem, we came across a guide on Stack Overflow that enabled us to convert the 3 letter codes into country names. Our second challenge was with the country code "CN" as SAS read the code as China, but our guide said China was "CHN" hindering our progress further. Thus, after gathering more information from online sources, we concluded that "CN" was actually Canada as Canada was missing from the initial SAS geo map. Lastly figuring out how to make an interactive dashboard as we have no prior experience was challenging. In the end, our hard work of staying in the university till 10 pm for multiple days resulted in a fruitful outcome.

### **7.3 The Lessons I Learned.**

From the project, I learned to work with colleagues situated in a different country through seamless communication and working in a team with an international member. Secondly, I learned how to

take a raw dataset and convert it into an insightful and visual report. Lastly, I learned how to navigate through SAS Viya to generate insightful dashboards. This report also gave me an idea of what an actual business analytics report might look like.

#### **7.4 Given the chance to start over, what would I do differently?**

If given the chance to start over, I wouldn't do anything differently as the journey of developing this project led me to gain more knowledge in the world of analytics and using software such as Python and SAS which are valuable for my career. If there had to be one thing that I had to change, I would change the way we delivered our presentation as it was not on par with the information, we could have provided due to the limited time. Overall, I am very satisfied and proud of what we as a team and I as an individual have achieved in this project.