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Modeling passenger preferences for air travel upgrades

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Group E

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Abstract: | The following machine learning project focuses on...

Introduction

Overview and Motivation

In the fast-paced world of air travel, airlines face a dual challenge: maintaining operational efficiency while personalizing the travel experience for their passengers. Key aspects that greatly influence passenger satisfaction include baggage handling, preferred seating, and in-flight meals. Each of these elements represents significant opportunities for airlines to enhance customer experiences and optimize their ancillary services.

The project aims to harness machine learning to predict and analyze passengers' choices regarding baggage, preferred seating, and in-flight meal options. By examining a range of influencing factors, such as trip duration and purpose, the project seeks to generate actionable insights that airlines can use to improve operational efficiency and tailor their services to individual customer preferences.

Our motivation stems from the logistical and customer service challenges faced by airlines when handling passengers' preferences efficiently. Accurate prediction models will help airlines anticipate the demand for different services, from baggage needs to specific seating and meal preferences. This, in turn, will allow them to allocate resources more effectively and design better marketing strategies, enhancing customer satisfaction and maximizing revenue from ancillary services.

Data

The dataset for our project is sourced from Kaggle and titled "Airlines Booking", compiled by user Anand Shaw. It is presented as a CSV file containing anonymized airline booking records, capturing a wide range of passenger data including flight details, baggage choices, preferred seat selection, and in-flight meal preferences. This comprehensive dataset provides the foundational data needed to analyze and understand the various preferences of air travelers, allowing us to identify patterns and predict future preferences. The dataset is accessible via Kaggle.

Related Work

Research on passenger preferences in air travel has highlighted several factors influencing travelers' choices and behaviors, notably service offerings like baggage handling, seat selection, and in-flight meal preferences. Ancillary and add-on revenues, such as those from baggage fees, preferred seating, and in-flight services, have become crucial for airline profitability [1]. The growth in these revenue streams underscores their importance in airline strategies, as ancillary revenues accounted for about 18% of total airline revenue in 2022 [2].

Baggage Preferences:

Studies indicate that baggage fees and policies greatly affect customer behavior. Clear communication about baggage policies can influence booking decisions, and flexibility in these policies can enhance customer loyalty. Research shows that ancillary baggage fees impact travelers' booking choices and willingness to pay [3], suggesting that transparent and adaptable baggage policies are crucial for maintaining customer satisfaction [3].

Preferred Seating:

Seat selection is critical for passenger comfort and satisfaction. Passengers value different seat attributes, such as proximity to exits, windows, or aisles, depending on their preferences. Research indicates that passengers are willing to pay extra for preferred seating, which underscores the importance of predictive models to cater to these preferences [4]. This willingness to pay highlights the revenue potential for airlines from charging for preferred seating [4].

In-Flight Meals:

The diversity in passengers' dietary and cultural preferences necessitates a variety of meal options to meet these needs. Studies show that offering diverse in-flight meal options can significantly improve passenger satisfaction [5]. Airlines that effectively address these preferences can differentiate their services, leading to higher customer satisfaction and loyalty[5].

In summary, the research on passenger preferences in air travel highlights the critical role of ancillary and add-on revenues such as baggage fees, preferred seating, and in-flight services. These elements not only significantly impact customer satisfaction but also contribute substantially to airline profitability. Clear communication and flexibility in baggage policies are essential for influencing booking decisions and enhancing customer loyalty. The willingness of passengers to pay extra for preferred seating and diverse in-flight meal options underscores the need for airlines to offer tailored services that meet diverse passenger preferences, ultimately driving higher customer satisfaction and loyalty.[1][2][3][4][5][6][7][8]

Research questions

Our study, "Modeling Passenger Preferences for Air Travel Upgrades," focuses on developing predictive models to determine passenger choices for additional services during air travel. The central research question explores the application of machine learning:

How can machine learning models utilize passenger demographic and trip-specific data to predict preferences for air travel upgrades such as extra baggage, preferred seating, and in-flight meals?

This question aims to uncover the potential of using various data points to accurately forecast which upgrades passengers are most likely to select, thereby enhancing personalized service delivery and operational efficiency.

Data

- **Sources**

As previously introduced, our study utilizes the "Airlines Booking" dataset curated by Anand Shaw and hosted on Kaggle. This dataset, provided in CSV format, is essential for our analysis aimed at modeling passenger preferences for air travel upgrades.

- **Description**

`num_passengers`: Indicates the total number of passengers traveling on the booking.

`sales_channel`: Specifies the platform or method through which the booking was made.

`trip_type`: Describes the type of trip (e.g., Round Trip, One Way, Circle Trip).

`purchase_lead`: Represents the number of days between the booking date and the travel date.

`length_of_stay`: The number of days the passenger intends to stay at the destination.

`flight_hour`: The hour of the day when the flight is scheduled to depart.

`flight_day`: The day of the week on which the flight is scheduled.

`route`: The flight route from origin to destination.

`booking_origin`: The country from which the booking was made.

`wants_extra_baggage`: A binary indicator (yes/no) if the passenger opted for extra baggage.

`wants_preferred_seat`: A binary indicator (yes/no) if the passenger chose a preferred seating option during booking.

`wants_in_flight_meals`: A binary indicator (yes/no) if the passenger requested in-flight meals.

`flight_duration`: The total duration of the flight in hours.

`booking_complete`: A flag indicating whether the booking was completed (yes/no).

The data has already been cleaned and is in good condition. However, further data processing will be conducted. This will involve removing any unnecessary data and encoding the data appropriately for use in our different models.

Exploratory Data Analysis (EDA)

EDA is a crucial step in understanding the underlying structure and patterns within our dataset. By employing various statistical and graphical techniques, EDA helps in identifying key relationships, trends, and anomalies that can inform further analysis and model development. In this section, we will explore the characteristics of our data on passenger preferences for air travel upgrades, focusing on how different features influence the choices for extra baggage, in-flight meals, and preferred seating. The insights gained from EDA will provide a solid foundation for building predictive models

Correlation Heatmap: Relationship Between Variables of Interest

The correlation heatmap visualizes the relationships between various variables related to passenger preferences for air travel upgrades. Each cell in the heatmap represents the correlation coefficient between two variables, with values ranging from -1 to 1. Darker shades of blue indicate a stronger positive correlation, while darker shades of red indicate a stronger negative correlation.

Key Observations:

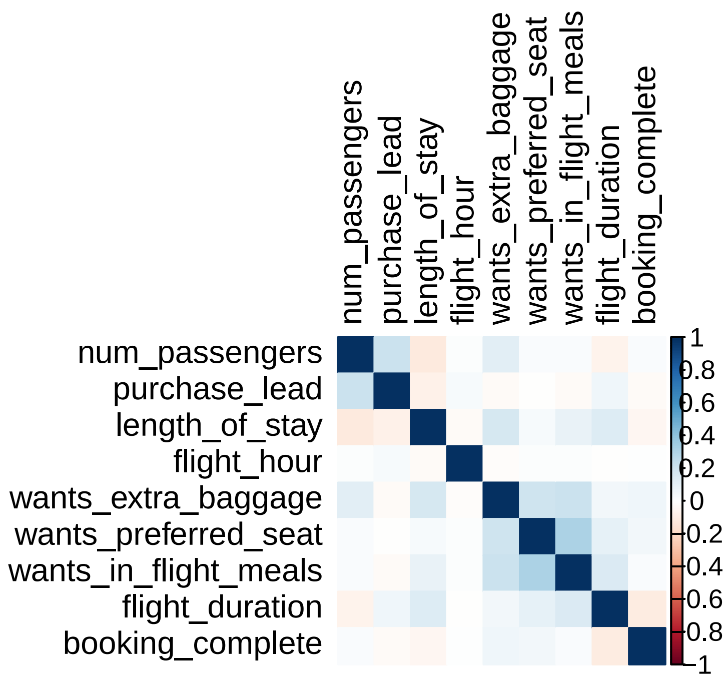
Length of Stay vs. Extra Baggage: There is a slight positive correlation, suggesting that passengers with longer stays tend to opt for extra baggage.

Purchase Lead vs. Extra Baggage: There is a noticeable negative correlation, indicating that passengers who book further in advance are less likely to select extra baggage.

Length of Stay vs. In-Flight Meals and Preferred Seats: Both show positive correlations, implying that longer stays increase the likelihood of choosing these services.

Purchase Lead vs. Preferred Seats and In-Flight Meals: Both show negative correlations, meaning advance bookers are less likely to choose these additional services.

This heatmap provides a clear overview of how different factors, such as trip duration and booking behavior, influence passengers' choices for ancillary services. Understanding these relationships can help airlines optimize their service offerings and improve customer satisfaction.



Target Variables (Y) vs. Predictive Features (X)

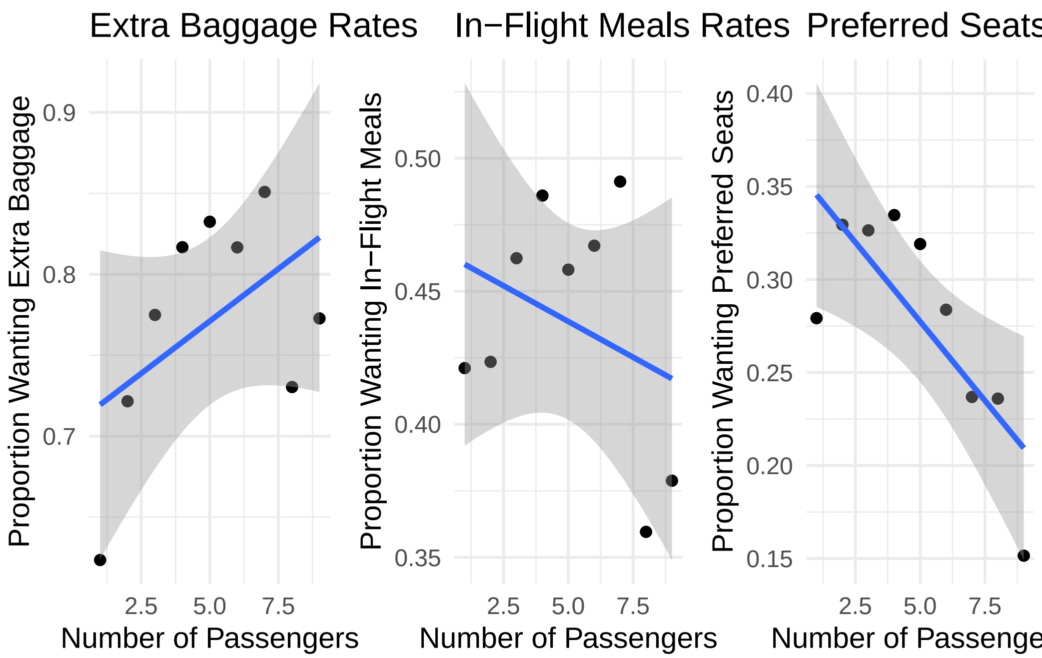
In this section, we examine the relationships between our target variables (Y) and various predictive features (X) to better understand passenger preferences for air travel upgrades. By analyzing these relationships, we aim to uncover patterns that can help predict the likelihood of passengers opting for additional services such as extra baggage, in-flight meals, and preferred seating. This analysis will provide valuable insights for airlines to enhance customer satisfaction and optimize their service offerings.

Number of Passengers and Service Preferences

Extra Baggage Rates: Positive trend; larger groups more likely to want extra baggage.

In-Flight Meals Rates: Slight negative trend; larger groups less likely to want in-flight meals.

Preferred Seats Rates: Clear negative trend; larger groups less likely to choose preferred seats. :::



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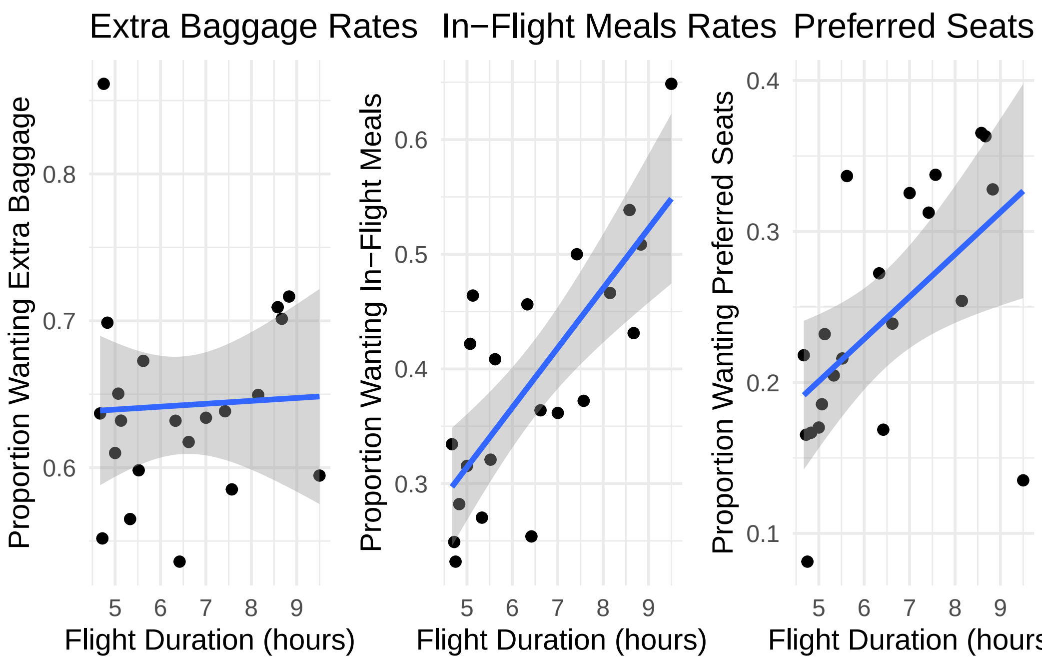
::: :::

Flight Duration and Service Preferences

Extra Baggage Rates: Slight positive trend; longer flights slightly increase extra baggage demand.

In-Flight Meals Rates: Clear positive correlation; longer flights increase in-flight meal demand.

Preferred Seats Rates: Positive correlation; longer flights increase preferred seat selection. :::



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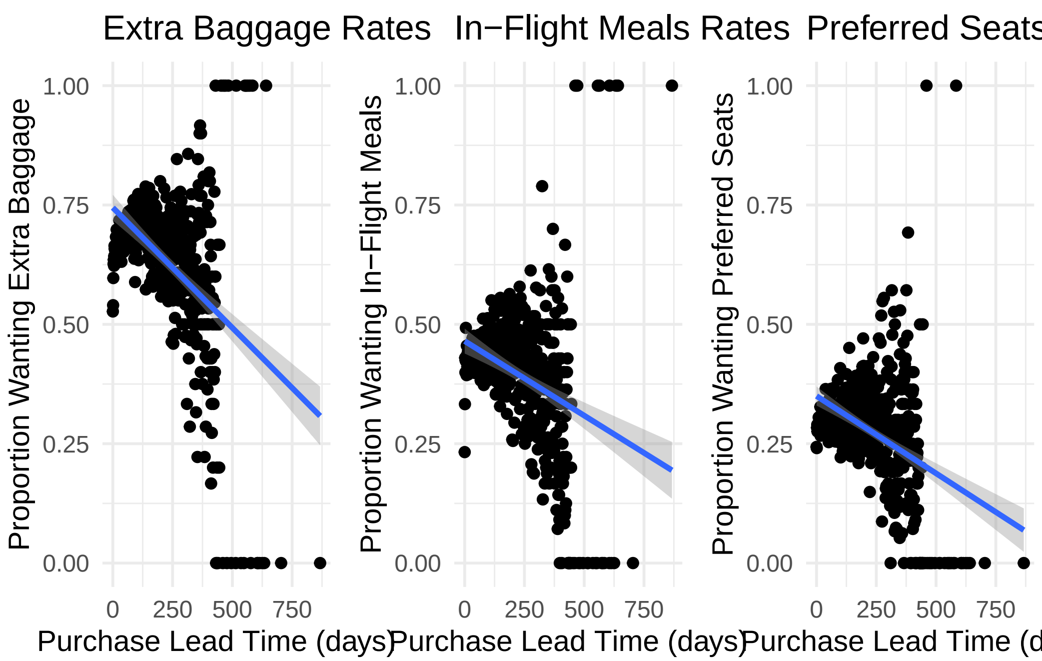
Purchase Lead Time and Service Preferences

Extra Baggage Rates: Negative trend; advance bookers less likely to want extra baggage.

In-Flight Meals Rates: Negative trend; advance bookers less likely to want in-flight meals.

Preferred Seats Rates: Negative trend; advance bookers less likely to select preferred seats. :::



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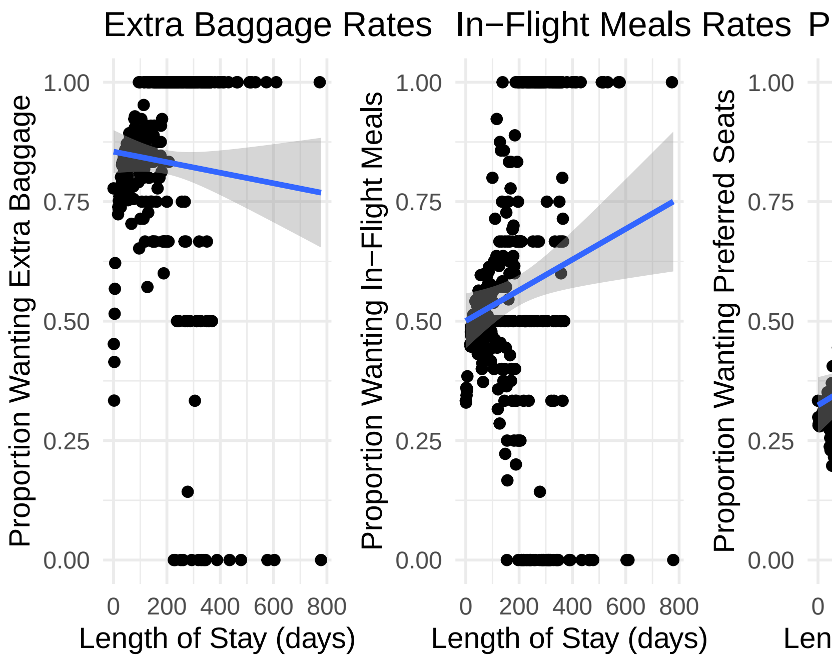
Length of Stay and Service Preferences

Extra Baggage Rates: Slight decrease as length of stay increases.

In-Flight Meals Rates: Positive correlation; longer stays increase the likelihood of wanting in-flight meals.

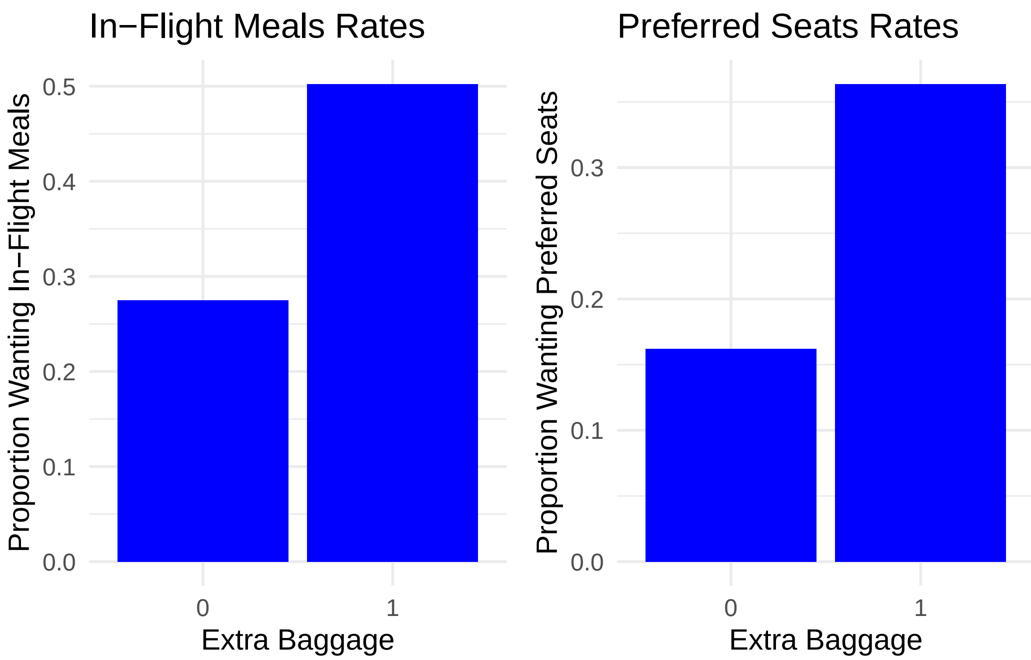
Preferred Seats Rates: Positive correlation; longer stays increase the likelihood of choosing pre-



ferred seats. ::: {.cell} ::: {.cell-output-display}
::: :::

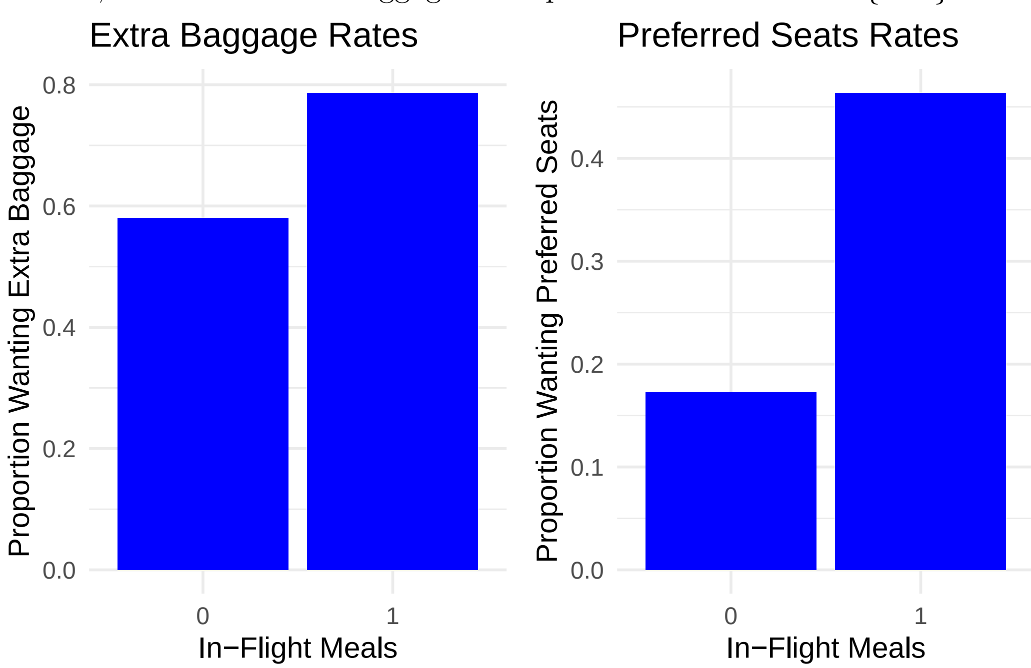
Relationship between variables of interest

The first set of graphs compares the proportion of passengers wanting extra baggage and in-flight meals based on their preferred seat selection. The left graph shows that a higher proportion of passengers with preferred seats (1) want extra baggage compared to those without preferred seats (0). Similarly, the right graph indicates that passengers with preferred seats are also more likely to want in-flight meals than those without preferred seats. This suggests a correlation between the desire for preferred seating and the preference for additional services such as extra baggage and in-flight meals. ::: {.cell} ::: {.cell-output-display}



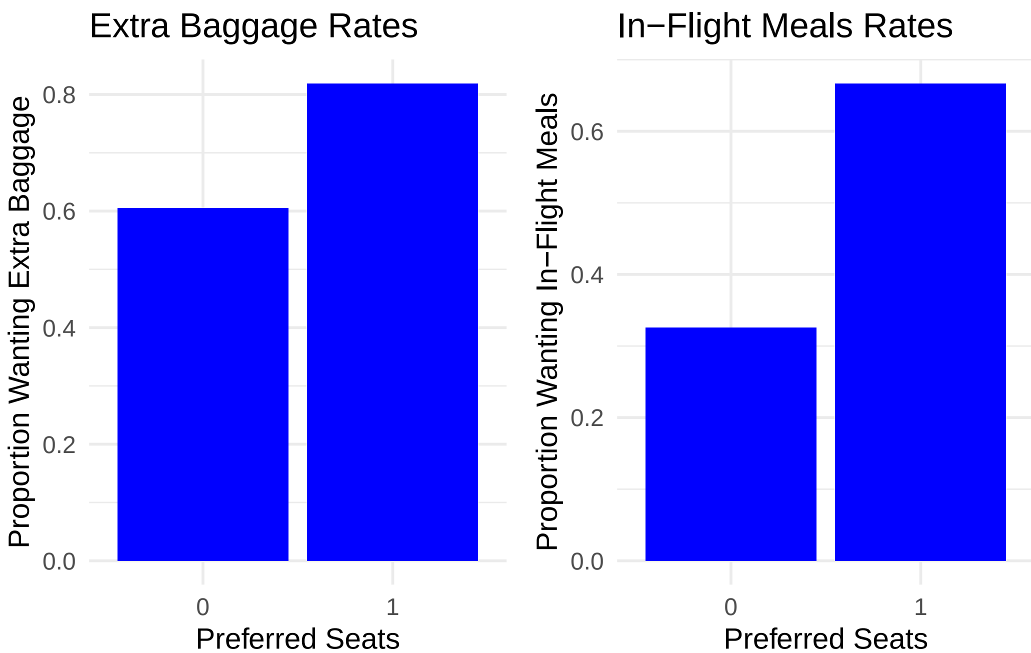
::: :::

The second set of graphs examines the proportion of passengers wanting extra baggage and preferred seats based on their in-flight meal preferences. The left graph demonstrates that passengers who opt for in-flight meals (1) have a higher proportion of wanting extra baggage than those who do not (0). The right graph reveals that passengers wanting in-flight meals are also more likely to choose preferred seats. This indicates that passengers' choice for in-flight meals is associated with a higher likelihood of selecting other additional services, such as extra baggage and preferred seats. ::: {.cell} ::: {.cell-output-display}



::: :::

The third set of graphs explores the proportion of passengers wanting in-flight meals and preferred seats based on their extra baggage preferences. The left graph shows that passengers opting for extra baggage (1) have a higher proportion of wanting in-flight meals compared to those who do not (0). The right graph indicates that passengers with extra baggage are also more inclined to select preferred seats. This implies that passengers' preference for extra baggage correlates with their likelihood of choosing in-flight meals and preferred seats. ::: {.cell} ::: {.cell-output-display}



::: :::

These visualizations highlight the interrelationships between various ancillary services, suggesting that passengers who opt for one additional service are more likely to opt for others.

Method

Supervised Learning

For our study on modeling passenger preferences for air travel upgrades, we selected three supervised machine learning techniques: logistic regression, random forest, and neural networks. Each of these models brings unique strengths and suitability for different aspects of our dataset.

Logistic Regression is a foundational tool in statistical modeling and machine learning, particularly adept at binary classification tasks. Its simplicity and interpretability make it a prime choice for initial explorations of binary outcomes such as determining whether a passenger would want extra baggage, to select a seat, or add a meal. Logistic regression provides clear insights through the statistical significance of variables and their coefficients, allowing us to understand the influence of each predictor on the response variable straightforwardly.

Random Forest is an ensemble learning technique that operates by building multiple decision trees and merging them together to obtain more accurate and stable predictions. It is particularly effective for handling datasets with complex structures and high dimensionality without requiring feature scaling. For multiclass classification issues, random forest can manage categorical variables and their interactions effectively, providing importance scores for each feature, which helps in interpreting the driving factors behind passenger preferences.

Neural Networks, with their deep learning capabilities, are well-suited for capturing complex and nonlinear relationships that other models might miss. This makes them extremely versatile for multilabel classification tasks, such as simultaneously predicting preferences across several categories like in-flight meals, seating, and baggage. Although they require more computational resources and are less interpretable than simpler models, neural networks can model intricate patterns in large-scale data, offering potentially higher accuracy and the ability to generalize across various types of data inputs.

Together, these models encompass a broad spectrum of analytical capabilities, from basic statistical inference to complex pattern recognition, ensuring our analysis is both robust and nuanced. This diversified approach not only enhances the accuracy of our predictions but also enriches our understanding of the data's underlying dynamics.

Data Preprocessing

Before applying the models, we preprocess the data to ensure it is in a suitable format for analysis. This involves removing columns that will not be of use in the models, encoding categorical variables, splitting the data into training and testing sets, and addressing class imbalances.

Removing Unneeded Columns

We remove columns that are not used in any models to streamline the data and reduce computational complexity. This step ensures that the models focus on relevant predictors and avoid overfitting due to irrelevant features or features that are not computationally efficient to create dummies for given their lack of importance.

```r
# R code for Logistic Regression
data_lr1 <- data |>
  dplyr::select(-route, -booking_origin, -departure, -arrival)
```

```python
# Python code for Random Forest and Neural Networks
data = data.drop(columns=['route', 'booking_origin', 'departure', 'arrival'])
```

Handling Categorical Variables

Categorical variables such as `sales_channel`, `trip_type`, `flight_day`, and `continent` are crucial for our analysis. We transform these variables into a format suitable for modeling through one-hot encoding in python and mutating as factors in R.

```r
# R code for Logistic Regression
categorical_vars <- c("sales_channel", "trip_type", "flight_day", "continent")
data <- data |>
  mutate(across(all_of(categorical_vars), as.factor)) |>
  dummy_cols(select_columns = categorical_vars, remove_first_dummy = TRUE)
```

```
# Python code for Random Forest and Neural Networks
# Prepare categorical variables with OneHotEncoder
categorical_vars = ['sales_channel', 'trip_type', 'flight_day', 'continent']
ct = ColumnTransformer([('one_hot_encoder', OneHotEncoder(), categorical_vars)], remaind
data_processed = ct.fit_transform(data)
```

Data Splitting

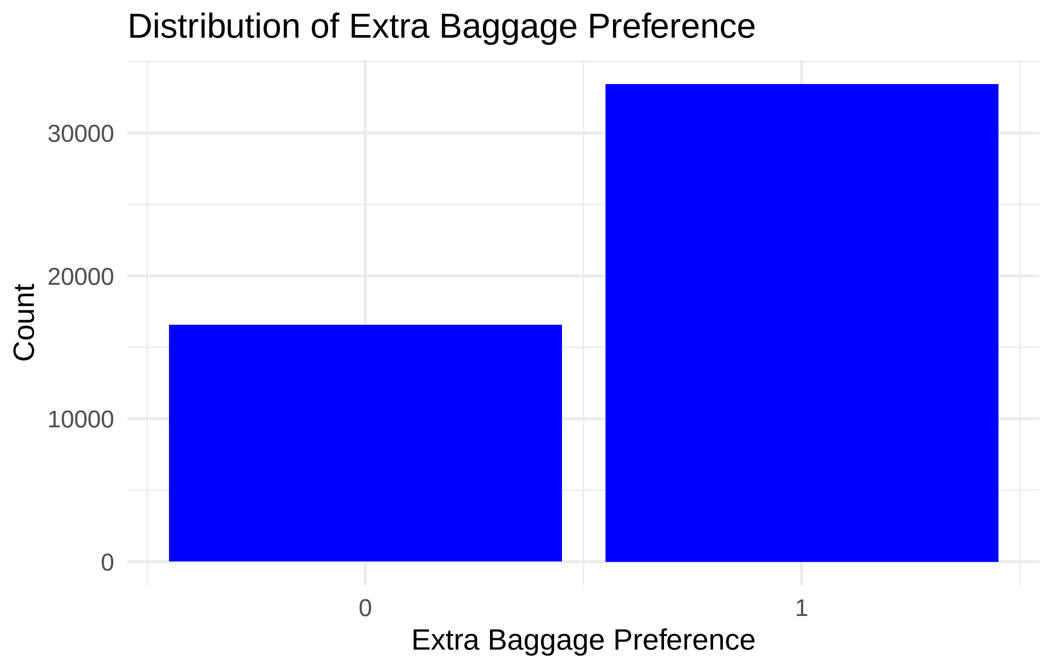
To ensure the reliability of our models, we split the data into training and testing sets. This division allows us to train the models on one subset and evaluate their performance on another, ensuring that the models generalize well to unseen data. We split at a 80/20 ratio to maintain a balance between training and testing data.

```
# R code for Logistic Regression
# Splitting data into training and testing sets
set.seed(123)  # for reproducibility
trainIndex <- createDataPartition(data_lr1$wants_extra_baggage, p = 0.8, list = FALSE)
train_data <- data_lr1[trainIndex, ]
test_data <- data_lr1[-trainIndex, ]
```

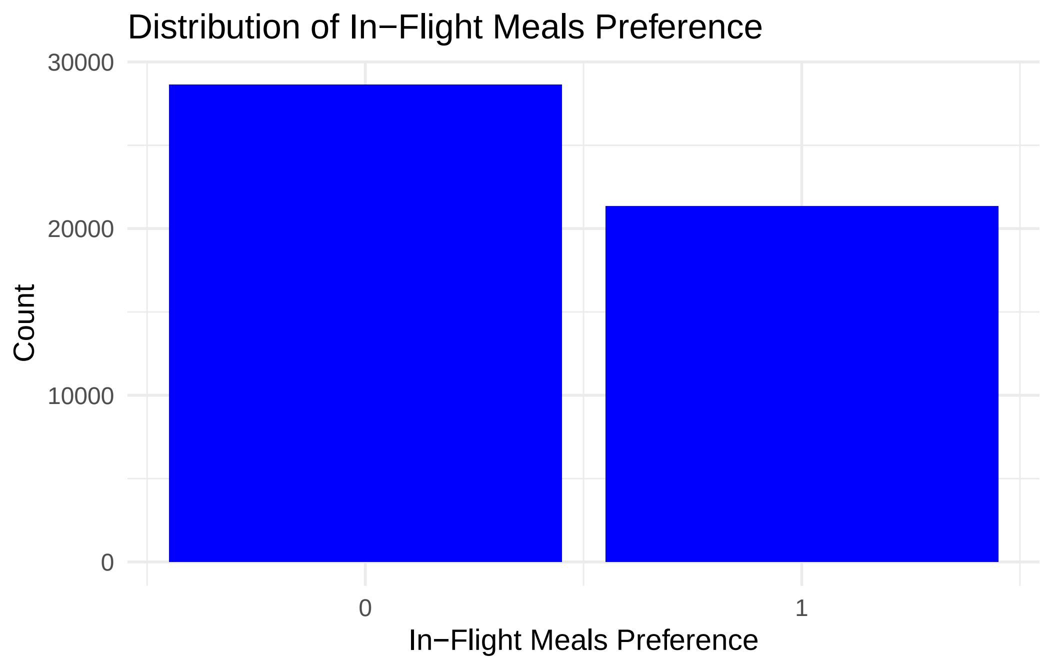
```
# Python code for Random Forest and Neural Networks
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=12
```

Addressing Class Imbalances

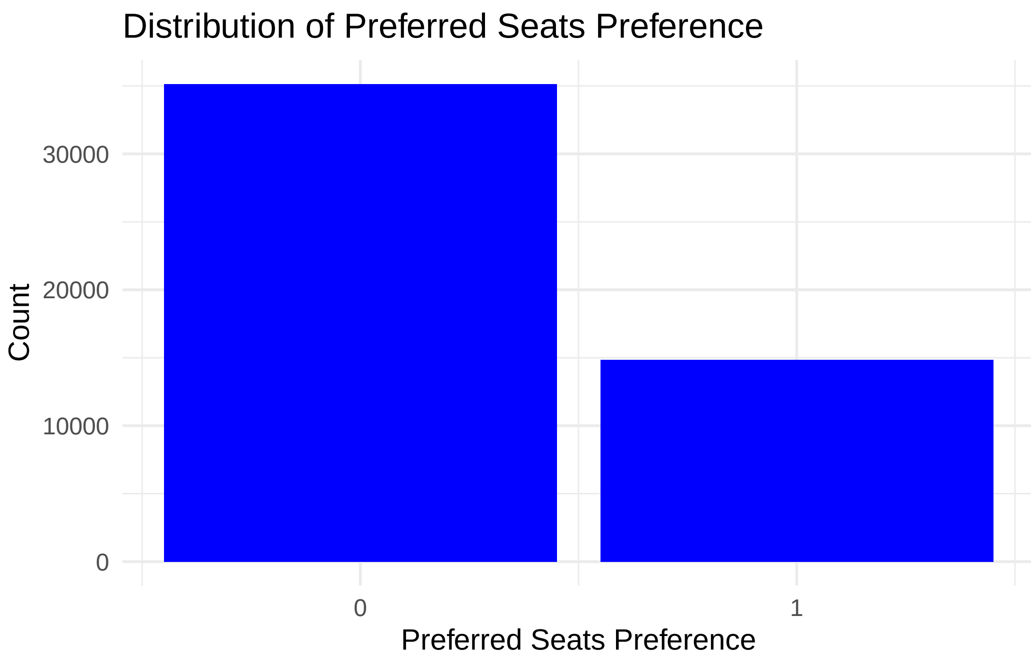
In our dataset, the classes are imbalanced, with some preferences being more prevalent than others. To address this issue, we use the techniques of downsampling or Synthetic Minority Over-sampling Technique (SMOTE) to balance the classes. This ensures that the models do not become biased towards the majority class and can make accurate predictions for all classes.



Note: The plot above shows the distribution of the target variable `wants_extra_baggage`*. There is a clear imbalance towards cases whereby customers often purchased extra baggage.*



Note: The plot above shows the distribution of the target variable `wants_in_flight_meals`*. In this case the data was more evenly distrubuted so we decided to leave the classes as they were.*



Note: The plot above shows the distribution of the target variable `wants_preferred_seat`. There is a clear imbalance towards cases whereby customers often did not purchase preferred seats.

To address the class imbalance, for both logistic regression and the neural network, we used downsampling, which involves randomly removing samples from the majority class to balance the class distribution. For the random forest model, we used the Synthetic Minority Over-sampling Technique (SMOTE), which generates synthetic samples for the minority class to balance the class distribution.

```
# Downsampling for wants_extra_baggage
train_data_baggage <- ovun.sample(wants_extra_baggage ~ ., data = train_data, method = "
# Downsampling for wants_preferred_seat
train_data_seat <- ovun.sample(wants_preferred_seat ~ ., data = train_data, method = "un
```

```
# SMOTE for Random Forest
# Handle class imbalance with SMOTE
smote = SMOTE(random_state=123)
X_train, y_train = smote.fit_resample(X_train, y_train)
```

Model Development and Tuning

This subsection outlines how each model is developed, including the initial setup, parameter tuning, and the specific adjustments made for each type.

Logistic Regression

The logistic regression model is developed using the `glm` function in R, with a focus on predicting the binary outcomes of `wants_extra_baggage`, `wants_in_flight_meals`, and wants_preferred_seat. 3 models were created to predict individually each outcome variable, the decision was made to not include any of the outcome variables in any of the models as they have such strong correlation between eachother. A stepwise backward elimination process based on the Akaike Information Criterion (AIC) was used to refine the model. This process helps identify the most relevant predictors and improve the model's performance by removing variables of lesser importance.

```
# Initial logistic regression model
logist_model1 <- glm(wants_extra_baggage ~ . - wants_preferred_seat - wants_in_flight_me
# Stepwise backward elimination based on AIC
reduced_model <- stepAIC(logist_model1, direction = "backward")
```

Random Forest

The Random Forest model is implemented using the RandomForestClassifier from the scikit-learn library in Python. For the implementation, we took advantage of its inherent capability to handle multiclass classification problems effectively. In the context of our study, where passengers can choose multiple services (such as extra baggage, preferred seating, and in-flight meals), each combination of choices represents a distinct class. This is often referred to as the "power set" of the outcome variables, essentially forming a grid of all possible combinations where each combination is treated as a unique class in a multiclass classification framework.

To accommodate this approach, we combine the outcome variables into a single multiclass target variable, where each unique combination of wants_extra_baggage, wants_preferred_seat, and wants_in_flight_meals is encoded into a distinct label. This transformation allows the Random Forest model to predict the exact combination of services a passenger is likely to choose, leveraging its capability to model complex interactions between features effectively.

```
# Ensure labels are combined into a single feature and converted to numeric
data['combined_label'] = pd.factorize(data['wants_extra_baggage'].astype(str) +
                                      data['wants_in_flight_meals'].astype(str) +
                                      data['wants_preferred_seat'].astype(str))[0]

# Append combined_label to processed data
data_processed['combined_label'] = data['combined_label']

# Define the RandomForest model using the specified parameters
model = RandomForestClassifier(random_state=123, n_estimators=250,       max_features=No

# Train the model
model.fit(X_train, y_train)

# Predict on the test data
predictions = model.predict(X_test)
```

Neural Network

The Neural Network model was implemented using the `Keras` library in Python, which provides a high-level neural networks API that allows for easy and flexible model building. In contrast to the Random Forest model, the Neural Network was utilized for its multilabel classification capabilities. Multilabel classification differs from multiclass classification in that each instance (passenger) can be assigned multiple labels (services) simultaneously, rather than being restricted to one out of many possible categories.

This approach aligns well with the nature of our data, where a passenger might opt for a combination of extras like baggage, seating, and meals without these choices being mutually exclusive. We structure the Neural Network to output multiple probabilities, one for each service, using a sigmoid activation function at the output layer to predict the likelihood of each service independently.

```
# Define the Neural Network model using the specified parameters
def create_model(input_dim, activation='relu', layers=2, dropout_rate=0.6):
    model = Sequential()
    model.add(Dense(64, activation=activation, input_dim=input_dim))
    model.add(Dropout(dropout_rate))
    for _ in range(1, layers):
        model.add(Dense(64, activation=activation))
        model.add(Dropout(dropout_rate))
    model.add(Dense(3, activation='sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model

# Create and train the model with the best parameters
model = create_model(input_dim=X_train.shape[1])
model.fit(X_train, y_train, batch_size=16, epochs=20, verbose=1)

# Predictions
y_pred_prob = model.predict(X_test)
y_pred = (y_pred_prob > 0.5).astype(int)
```

Parameter Tuning

Parameter tuning and cross-validation are critical components in developing robust machine learning models, ensuring that the models not only fit the training data well but also generalize effectively to new, unseen data. Here, we'll detail how these methodologies were applied across the logistic regression, random forest, and neural network models.

For **logistic regression**, the tuning process primarily involved feature selection rather than hyperparameter tuning. We utilized the stepwise backward elimination process based on AIC, which is a methodological approach to select the most significant predictors by iteratively removing the least important ones. While this doesn't involve adjusting the hyperparameters of the logistic regression model, it is crucial for optimizing the model's performance by reducing complexity and preventing overfitting.

Wants Extra Baggage Reduced Logistic Regression Model

```
Call:
glm(formula = wants_extra_baggage ~ num_passengers + purchase_lead +
    length_of_stay + flight_duration + booking_complete + sales_channel_Mobile +
    trip_type_RoundTrip + continent_Americas + continent_Asia +
    continent_Europe + continent_Oceania + continent_Unknown,
    family = "binomial", data = train_data_baggage)

Coefficients:
                       Estimate Std. Error z value Pr(>|z|)
(Intercept)           0.0913672  0.4435681   0.206  0.83680
num_passengers        0.3849043  0.0150967  25.496  < 2e-16 ***
purchase_lead        -0.0009681  0.0001441  -6.719 1.83e-11 ***
length_of_stay        0.0218910  0.0006757  32.397  < 2e-16 ***
flight_duration       0.0426705  0.0094419   4.519 6.21e-06 ***
booking_complete      0.5605726  0.0384982  14.561  < 2e-16 ***
sales_channel_Mobile -0.2426398  0.0403090  -6.019 1.75e-09 ***
trip_type_RoundTrip  -0.4184208  0.1294748  -3.232  0.00123 **
continent_Americas   -1.3624296  0.4338744  -3.140  0.00169 **
continent_Asia       -0.9875319  0.4178979  -2.363  0.01812 *
continent_Europe     -1.2087295  0.4350705  -2.778  0.00547 **
continent_Oceania    -0.8955288  0.4179542  -2.143  0.03214 *
continent_Unknown    -1.3480895  0.5156720  -2.614  0.00894 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 36834  on 26569  degrees of freedom
Residual deviance: 34345  on 26557  degrees of freedom
AIC: 34371

Number of Fisher Scoring iterations: 5
```

Above shows the reduced model for ***wants_extra_baggage****, all predictor variables are significant and the model was reduced to 12 variables, in particular it is interesting that the day of the week has no real consequence on the outcome of whether a customer wants extra baggage or not. The AIC stands at 34371 after the variable reduction.*

Wants Preferred Seat Reduced Logistic Regression Model

```
Call:
glm(formula = wants_preferred_seat ~ length_of_stay + flight_hour +
    wants_extra_baggage + flight_duration + booking_complete +
```

```
    sales_channel_Mobile + trip_type_OneWay + flight_day_Thu +
    flight_day_Tue + continent_Americas + continent_Asia, family = "binomial",
    data = train_data_seat)

Coefficients:
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)          -1.661425   0.087553 -18.976  < 2e-16 ***
length_of_stay       -0.001698   0.000389  -4.366 1.27e-05 ***
flight_hour           0.006459   0.002493   2.591  0.00957 **
wants_extra_baggage   1.080755   0.031138  34.709  < 2e-16 ***
flight_duration       0.128070   0.009843  13.012  < 2e-16 ***
booking_complete      0.381940   0.038541   9.910  < 2e-16 ***
sales_channel_Mobile  0.366482   0.042489   8.625  < 2e-16 ***
trip_type_OneWay     -0.308053   0.155181  -1.985  0.04713 *
flight_day_Thu       -0.080591   0.038629  -2.086  0.03695 *
flight_day_Tue       -0.106578   0.038301  -2.783  0.00539 **
continent_Americas   -0.186436   0.130813  -1.425  0.15410
continent_Asia       -0.253656   0.030307  -8.369  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 33033  on 23827  degrees of freedom
Residual deviance: 31209  on 23816  degrees of freedom
AIC: 31233

Number of Fisher Scoring iterations: 4
```

*Above shows the reduced model for **wants_preferred_seat**, most predictor variables are significant and the model was reduced to 11 variables, the remaining variables are very different from **wants_extra_baggage**, which is interesting as they share such correlation. The AIC stands at 31233 after the variable reduction.*

Wants In-Flight Meals Reduced Logistic Regression Model

```
Call:
glm(formula = wants_in_flight_meals ~ num_passengers + purchase_lead +
    length_of_stay + flight_hour + wants_extra_baggage + wants_preferred_seat +
    flight_duration + booking_complete + sales_channel_Mobile +
    trip_type_RoundTrip + flight_day_Mon + flight_day_Tue + flight_day_Wed +
    continent_Americas + continent_Asia + continent_Europe +
    continent_Oceania + continent_Unknown, family = "binomial",
    data = train_data)

Coefficients:
```

```
                      Estimate Std. Error z value Pr(>|z|)
(Intercept)         -2.1018812  0.3367570  -6.242 4.33e-10 ***
num_passengers       0.0368962  0.0111409   3.312 0.000927 ***
purchase_lead       -0.0005680  0.0001272  -4.467 7.95e-06 ***
length_of_stay       0.0029135  0.0003445   8.458  < 2e-16 ***
flight_hour          0.0075975  0.0020350   3.733 0.000189 ***
wants_extra_baggage  0.6947210  0.0248461  27.961  < 2e-16 ***
wants_preferred_seat 1.2619666  0.0241095  52.343  < 2e-16 ***
flight_duration      0.1497557  0.0080219  18.668  < 2e-16 ***
booking_complete     0.1689283  0.0315341   5.357 8.46e-08 ***
sales_channel_Mobile -0.1295023 0.0355612  -3.642 0.000271 ***
trip_type_RoundTrip  0.4334617  0.1120420   3.869 0.000109 ***
flight_day_Mon      -0.0594067  0.0311158  -1.909 0.056235 .
flight_day_Tue      -0.0709124  0.0318852  -2.224 0.026149 *
flight_day_Wed      -0.0565953  0.0316766  -1.787 0.073992 .
continent_Americas  -1.1033984  0.3285006  -3.359 0.000783 ***
continent_Asia      -0.8191083  0.3106376  -2.637 0.008368 **
continent_Europe    -0.9169358  0.3266989  -2.807 0.005006 **
continent_Oceania   -0.5285831  0.3106931  -1.701 0.088886 .
continent_Unknown   -0.8084988  0.4126927  -1.959 0.050103 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 54604  on 39999  degrees of freedom
Residual deviance: 48565  on 39981  degrees of freedom
AIC: 48603

Number of Fisher Scoring iterations: 4
```

Above shows the reduced model for `wants_in_flight_meals`, most predictor variables are significant and the model was reduced to 18 variables, a lot more than the previous two. The AIC stands at 48603 after the variable reduction.

Cross-validation was also employed for logistic regression to ensure the model's stability and reliability. By partitioning the data into multiple subsets, we could train and validate the model multiple times on different segments of the data, which helps in assessing how the model will perform across different samples of the dataset.

For the **Random Forest model**, extensive hyperparameter tuning was conducted using grid search cross-validation. This method systematically goes through multiple combinations of parameters, allowing us to find the best settings for parameters such as the number of trees (n_estimators), the maximum depth of the trees (max_depth), and the minimum number of samples required to split a node (min_samples_split). This approach is vital for fine-tuning the model to enhance its accuracy and efficiency.

```
from sklearn.model_selection import GridSearchCV

# Define parameter grid focusing on fewer trees and tree complexity
param_grid = {
    'max_features': ['sqrt', 'log2', None],  # Features considered for splitting at each
    'min_samples_split': [10, 20],  # Minimum number of samples required to split an int
    'min_samples_leaf': [5, 10]  # Minimum number of samples required to be at a leaf no
}

# GridSearchCV for parameter tuning
grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=10, scoring='accur
grid_search.fit(X_train, y_train)

# Best parameters
print("Best parameters:", grid_search.best_params_)
```

Cross-validation was embedded in the grid search process, where each parameter combination was validated across multiple folds of data, ensuring generalizability of the model.

Similarly, for the **Neural Network**, grid search cross-validation was used to optimize several hyperparameters including the number of layers, the number of neurons in each layer, dropout rates, and activation functions. This fine-tuning is crucial for deep learning models due to their complexity and the large number of training configurations possible.

```
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import GridSearchCV

# Function to create model, for use in KerasClassifier
def create_model(layers=1, activation='relu', dropout_rate=0.2):
    model = Sequential()
    model.add(Dense(64, activation=activation, input_dim=X_train.shape[1]))
    model.add(Dropout(dropout_rate))
    for i in range(1, layers):
        model.add(Dense(64, activation=activation))
        model.add(Dropout(dropout_rate))
    model.add(Dense(3, activation='sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model

# Parameter grid
param_grid = {
    'epochs': [20, 50],
    'batch_size': [16, 32],
    'layers': [1, 2],
    'activation': ['relu', 'tanh'],
    'dropout_rate': [0.5, 0.6]
```

```
}

best_score = 0
best_params = {}

for params in ParameterGrid(param_grid):
    # Separate model parameters and training parameters
    model_params = {key: params[key] for key in params if key in ['layers', 'activation'
    train_params = {key: params[key] for key in params if key in ['epochs', 'batch_size'

    model = create_model(input_dim=X_train.shape[1], **model_params)
    model.fit(X_train, y_train, **train_params, verbose=0)
    score = model.evaluate(X_test, y_test, verbose=0)[1]  # Get accuracy
    if score > best_score:
        best_score = score
        best_params = params

print("Best score: {:.2f}".format(best_score))
print("Best parameters:", best_params)
```

The use of cross-validation in this context ensures that the neural network's performance assessment is not only based on a single train-test split but rather on multiple folds, thus providing a more robust estimate of the model's performance on unseen data.

These strategies collectively help in developing models that are not only tuned to perform well on the training data but also fit to handle new, unseen data effectively.

Note: Computational resources and time constraints limited the exhaustive search for optimal hyperparameters. In practice, it is essential to balance the trade-off between model performance and computational efficiency.

Model Evaluation

After training and tuning the models, we evaluated their performance using metrics to assess their predictive capabilities. For each model, we calculated the following metrics:

1. **Accuracy**: The proportion of correctly classified instances out of the total instances. It provides a general overview of the model's performance.
2. **AUC**: The area under the receiver operating characteristic (ROC) curve, which measures the model's ability to distinguish between classes. A higher AUC indicates better performance.
3. **Precision**: The proportion of true positive predictions out of all positive predictions. It measures the model's ability to avoid false positives.
4. **Recall**: The proportion of true positive predictions out of all actual positives. It measures the model's ability to capture all positive instances.

Interpretation of Results

The evaluation metrics for each model are summarized below:

- Interpretation of the model(s)

Unsupervised learning

- Clustering and/or dimension reduction

Conclusion

- Brief summary of the project
- Take home message
- Limitations
- Future work?

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