Setup

1.1Topic and research question

This study explores the challenge of forecasting whether a reservation will be made by online or offline methods, using a wide range of data characteristics. The classification of online and offline bookings is highly significant in the hospitality business, as it reveals diverse consumer habits and preferences that have a direct impact on marketing strategies, resource allocation, and customer relationship management. Precisely identifying the booking route can offer valuable insights that empower stakeholders at different levels.

By developing effective pricing and inventory strategies based on an understanding of reserving trends, hotel management can maximize room occupancy and boost revenue. Through the customization of campaigns and special offers, marketing teams can effectively target specific customer segments, thereby increasing conversion rates and customer engagement. These predictions can be employed by analysts and data scientists to improve predictive models and identify emerging trends in customer booking patterns.

1.2. Dataset

The dataset includes both numerical (integers and floats) and categorical (objects) types. The categorical data need to be encoded. Some data are not useful and could be dropped, such as the day of the week and booking IDs. If the distribution between 'Online' and 'Offline' in the market segment type. It might bias the model towards the majority class. Features like ‘number of weekend nights’ and ‘number of week nights’ might be highly correlated with the total stay or with the ‘average price’. High correlation can lead to multicollinearity issues in some models, although logistic regression is generally robust to this. Extreme values in features like average price or lead time can skew the model's understanding and predictions. These need to be handled appropriately, either by normalization or by applying robust methods.

1.3. Modelling agreements

The criteria we chose are F1 and recall. When evaluating the performance of a classification model, F1 score and recall are two such metrics that are often used in machine learning. Recall is defined as a measure of the proportion of actual positives that are correctly identified. The F1 score is defined as the harmonic mean of precision and recall. It conveys the balance between precision and recall through a number. Essentially, it's calculated as 2 * (Precision * Recall) / (Precision + Recall).(Chicco & Jurman, 2020)

Among the research questions, the scenario of predicting the hotel's online and offline booking types is particularly suitable for using the two evaluation indicators of recall (Recall) and F1 score (F1 Score). Recall reduces the loss of important reservations and ensures that the prediction model misses as few as possible For a small but important number of offline bookings, recall rate will be a key metric. For example, if offline bookings may involve large groups or VIP customers, these bookings may have a significant impact on the hotel's revenue and operations. In this case, high recall means that the model is able to capture these key reservations. The F1 score can comprehensively reflect the model's ability to predict accuracy and completeness in handling actual business scenarios. This is particularly important for hotel managers, who need to ensure that all booking types are processed efficiently while avoiding incorrect bookings.

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1. Predictive Model: Logistic regression

1.1 Model Description

The model I use is logistic regression. The logistic regression usually fits the binary classification problem. Typically, if the predicted probability is greater than 0.5, the data is classified into the positive class; otherwise, it is classified into the negative class. The predicted labels are two classes which are "Online" and "Offline". These labels could be encoded to numerical labels such as 0 and 1.

1.1.1 Assumptions of linear regression

The target data is binary. The observations are independent. No Multicollinearity of the training dataset. There are no extreme outliers. There is a linear relationship between the training dataset and the testing dataset. The dataset is large enough.

1.1.2 Strengthens and Limitations:

Strengthens:

- Multicollinearity: The data has attributes for describing the features of visitors to the hotel. The attributes do not correspond with each other by their meaning. On the other hand, the correlations have been shown from the previous report stage 1, heatmap.
- Large sample size: The adequate variables in the data set. Logistic regression requires a large number of observations.

Limitations:

- Linearity: It is not sure that there is linearity between the dependent variable and the independent variables.
- Outliers: There are clear outliers for several features: "Number of weeknights", "number of children.", "lead time", and"average price" from boxplot. These outliers might effect the performance of logistic regression since it is sensitive to the outliers.

Justifications:

According to those assumptions of the regular logistic regression, it should be fine used for the current hotel booking data set.

1.2 Model Algorithm

1.2.1 Underlying principles of logistic regression:

Logistic regression is a classification model, that particularly performed well on binary class. The sigmoid function:

$$\sigma(z)= \frac{1}{1+e^{-z}} \text{ ,where } z=w0+w1x1+w2x2+...+wnxn$$

w indicates the weights corresponding to the features $x1, x2, \ldots, xn$, *respectfully.*

1.2.2 The logistic function coodinate any real-valued number to the range [0, 1], so they will be able to transit for representing probabilities.

1.2.3 Hyperparameters:

- One Hot Encoding: The method converts values into categorical columns. It signs a new binary column for each category of the variable. The best suitable case is that the nominal data do not have any relationship between the categories which leads models to perform better by treating each category as an independent feature. It is usually suitable for logistic regression. However, it has disadvantages that the method will increase the dimensions which might lead to model complexity.
- Label Encoding: The Label encoding converts each category into an integer value. It is usually used for conducting some labels that have some relationship. For example, online or offline when they are target features.
- Solvers: Solvers are optimizations in the scikit learn for logistic regression which can minimize the cost function by using optimized gradient decent methods.
- Penalties: The default penalty we set for this problem is set as L2. The typical L1 and L2 impose penalties to the coefficients so the model could be generalized and prevent models' overfitting. L1 indicates Lasso regression. It generalized the less important features' coefficient to true zero. It could be useful if there are a lot of features. One case is that the useful features are much less than the total.

Another case is the number of features is much more than the sample size. L2 indicates Ridge regression. It generalized the less important features' coefficient close to zero. In this way, the model is less complex but keeps useful information.

- Maximum Iterations: There is a maximum number of iterations for the grid search taken.
- Random_state: A fixed number signed to random_state guarantees that the same data splits, parameter initializations, or random selections happen in the same way each time when running the code.

1.2.4 Algorithm Execution: (Appendix)

1.2.5 Discussion on recent advancements or adaptations:

The recent logistic regression can use updated techniques, such as scalability, and optimizing solvers for reducing the loss, which let the logistic regression be used on more types of datasets. In the dataset chosen, the experiment should be taken for comparison of which parameters or which combination of parameters will work the best.

Besides, the logistic regression can be integrated into some neural network architectures, enabling end-to-end learning and improved predictive performance. (reference)

1.3 Model Development

1.3.1 Data Preprocessing:

a. Use One Hot Encoding method to conduct only categorical data into numerical data in the sample without the target feature. The method fits the data in the sample well, because of the multicollinearity of the logistic regression.
b. Label Encoding: The target "online" and "offline" is encoded to label as 0 and 1. The features are inverse of each other which means they have inverse relationships. The label Encoding transforms the target features and will not increase the computing complexity.
c. Feature Scaling: Use StandardScaler after the categorical data in the sample that has been one hot encoding.
d. Data split: Data is divided into training set, validation set, and testing sets to ensure the model's ability to generalize to unseen data. The data is split into 60% for training, 20% for validation, and 20% for testing. It is a common procedure if the data is split to 80% and 20% according to Pareto principle(Grosfeld-Nir, et al.). The validation set can be used to tune parameters and select the best model without using the test set, which should only be used to assess the model's final performance.

1.3.2 Python Functions:

- LogisticRegression(): Builds the logistic regression model. The insert parameters are max_iter"=1000, solver="sag", random_state=43
    - The iterations are 1000 for each search.
    - The default solver for this problem is set as "sag". "sag" stands for Stochastic Average Gradient descent (SAG). It stores and updates a simple average of the most recent gradients for each training example. The method is good at optimizing the large dataset. However, the best parameter might not be SAG. The best parameter should be decided by the output of the grid search.
    - The random_stats is 43. It ensures that each output will have the same result.

2. Model Evaluation and Optimization

2.1 Model Evaluation

2.1.1 Confusion matrix

The confusion matrix is used to evaluate the performance of the fitting model. The values of True Positive (TP), True Negative (TN), Positive (FP), False Negative (FN) in the graph could clearly explain the performance of the model. The label 0 is confused by the classification to the label 1 is 534/(1549+534) which is around 25.6%. The label 1 is confused by the classification to the label 0 is 529/(529+4139) which is 11.3%. The precision and recall are almost the same so the overfitting seems not happen.

2.1.2 Classification report

Classification report is used to evaluate model performance, focusing on accuracy, precision, recall, and F1-score. The precision is 0.75 for class 0 and 0.89 for class 1. The Precision score and recall values are almost the

same. It seems that overfishing does not happen. $F1=2\times(\text{precision}+\text{recall})/(\text{precision}\times\text{recall})$ which shows the balance of the precision and recall values. Overall, the logistic regression has better performance on class 1.

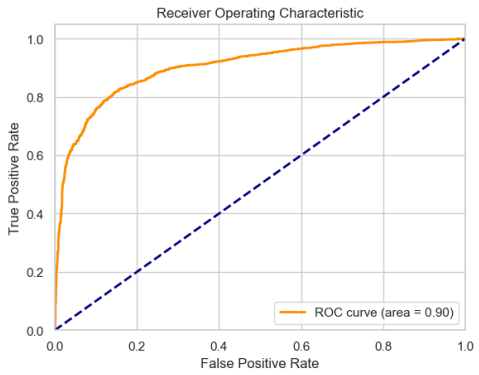
2.1.3 Receiver Operating Characteristic curve(ROC curve)

The AUC for your ROC curve is 0.90. This is a high value, suggesting that the model has a good measure of separability. An AUC of 0.90 means there is a 90% chance that the model will be able to distinguish between positive class and negative class.

```
Confusion Matrix:
 [[1549  534]
 [ 529 4139]]
Classification Report:
              precision    recall  f1-score   support

           0       0.75      0.74      0.74      2083
           1       0.89      0.89      0.89      4668

    accuracy                           0.84      6751
   macro avg       0.82      0.82      0.82      6751
weighted avg       0.84      0.84      0.84      6751
```



Model Optimization

2.2.1 GridSearchCV(): The grid search is used to find the highest accuracy and coordinates the best parameters. The “lbfgs”,”newton-cg”,”sag”,”saga” is applied as the parameters tuning for the grid search. The paneities of the parameters are L1 and L2. The strength of the “c” are the list from 0.01 to 100.

- Solvers: In the grid search of the model: Solvers include “lbfgs”, “newton-cg”, “sag”,”saga” will be applied. The “lbfgs”, “newton-cg”, “sag” supports only L2. In the grid search, if the solver does not support the penalty, the round will be directly skipped and would not affect the whole grid search approach.
    - “lbfgs”: Limited-memory Broyden-Fletcher-Goldfarb-Shanno algorithm. The L-BFGS uses a limited amount of computer memory. It's good for small to medium-sized datasets.
    - “newton-cg”: Newton's method for optimizing, also known as the Newton conjugate gradient method. It is speedy for small- to medium-sized datasets but requires computing the second derivatives, so it is much more intensive-computationally.
    - "sag": Stochastic Average Gradient descent. Only a random subset of the full dataset is used to compute the gradients at each iteration. It's efficient for large datasets and supports only L2 regularization.
    - “saga”: Stochastic Average Gradient Augmented that supports both L1 and L2 regularization,
- Penalties: L1, L2 will be applied. The discuss of the type of penalties is covered in the Model Algorithms.
- “C” represents the inverse of regularization strength. The smaller value, the stronger the regulations. For example: The value of 0.01 might not capture all the patterns in the data, potentially leading to higher bias but lower variance. Inversely, the 100 will capture the data probably including noise which might lead to over fitting.
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2.2.2 Outliers: The outliers has been removed from the detect of the boxplot. The codes then could been add to the front to achieve better performance. It can been see that the precision score increase from 88 to 89. The method to remove outliers is : velues below $Q1-1.5\times IQR$, will be set to $Q1-1.5\times IQR$, *values above* $Q3+1.5\times IQR$ will be set to $Q3+1.5\times IQRQ3+1.5\times IQR$.

Discussion

One of the greatest advantages of decision trees is their high interpretability. The model's decision-making process can be visually displayed through a tree diagram. and can handle non-linear relationships. For limitation, decision trees are very prone to overfitting, especially when the tree is very deep or does not have proper pruning. Decision trees are very sensitive to small changes in the data and make the prediction results of a single decision tree potentially unstable.

The Random Forest model is renowned for its robustness, as it is less prone to overfitting in comparison to individual decision trees. Furthermore, it has remarkable scalability, effectively handling extensive datasets filled with numerous variables without requiring the elimination of any. Nevertheless, it has several restrictions; its intricacy surpasses that of decision trees, which could potentially escalate computational requirements and prolong processing time. Furthermore, the intricate nature of the model can reduce its interpretability.

We evaluated the Logistic Regression algorithm for our dataset. Strengths include a lack of multicollinearity and a large sample size of 23,626 observations, which supports robust model training. However, the model faces challenges due to the dataset's high dimensionality and uncertainty in the linearity between variables. Additionally, significant outliers in features such as "number of weeknights" could negatively impact the model's performance, as Logistic Regression is sensitive to outliers.

model	recall	f1-score
Decision tree	0.91	0.91
Random Forest	0.93	0.93
logistic regression	0.89	0.89

Quantitative comparison: Recall: Random forest shows the highest recall, which is 0.93. This shows that among the three models, Random Forest is the most effective in identifying cases below the scheduled line. The recall rate of the decision tree follows closely at 0.91, and its performance is also very good. Logistic regression has a relatively low recall rate of 0.89, which may mean it is the worst at avoiding missing positive classes.

F1-Score: Random Forest also performed best on F1-score of 0.93, which reflects that it achieves the best balance between precision and recall. The F1 score of the decision tree is 0.91, which is a good performance. Logistic regression has an F1 score of 0.89, which is the lowest, indicating that it is the weakest at balancing precision and recall.

Qualitative comparison: Random forests are generally more complex than decision trees and may require more computing resources, but therefore provide more stable performance. Decision trees are relatively simple and intuitive, easy to understand and explain, but may face the risk of overfitting. Logistic regression provides good interpretability, but may not be as effective as tree models when dealing with complex or nonlinear relationships.

Wider implications for the research question: In predicting hotel reservations, high-recall model random forest can help ensure that almost all important offline reservations are identified, which can ensure customer satisfaction and optimize hotel revenue. A model with a high F1 score ensures that while accurately identifying booking types, it misses as few important bookings as possible, helping to maintain service quality and customer relationships.

Conclusion

Our thorough assessment of decision trees, Random Forest, and Logistic Regression models for predicting hotel bookings concludes that there are clear benefits and difficulties associated with each. The Random Forest model demonstrates great effectiveness by achieving the maximum recall and F1-score of 0.93, suggesting its exceptional performance in accurately detecting and balancing booking kinds. Although decision trees are highly interpretable and user-friendly, they are susceptible to overfitting and exhibit lower stability. Although Logistic Regression is known for its interpretability, it is not effective in dealing with complicated datasets and non-linear relationships. Considering the crucial importance of precisely identifying bookings to maximize income and customer happiness, it is advisable to use the Random Forest model because of its strong accuracy. Potential future investigations may involve optimizing tree-based models, and improving data collection techniques to minimize outliers.

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Appendix

Pseudo code for the Decision Tree algorithm

```
Function BuildDecisionTree(Dataset):
    If all records in the dataset have the same target variable value:
      -> Return a leaf node with the label of that common value
   If there are no features left to split on:
      -> Return a leaf node with the label of the most common target variable value in the dataset
   Select the best splitting feature:
      For each feature in the dataset:
         For each possible value of the feature:
            Split the dataset based on that feature value
            Evaluate the effectiveness of the split (typically using Gini impurity or information gain)
         Record the best split effectiveness for that feature
      -> Choose the feature with the best split effectiveness for division
   Using the selected feature and corresponding best split point, divide the dataset into subsets
   Recursively call BuildDecisionTree function on each subset
   Create a decision node linked to the subtrees generated in the steps above
   Return the decision node
```

(cs.cmu.edu)

Pseudo code for the Random Forest algorithm

```
To generate c classifiers:
for i = 1 to c do
  Randomly sample the training data D with replacement to produce D_i
  Create a root node, N, containing D_i
  Call BuildTree(N)
end for
BuildTree(N):
```

if N contains instances of only one class then

return

else

Randomly select x% of the possible splitting features in N

Select the feature F with the highest information gain to split on

Create child nodes of N, N_1, ..., N_F, where F has f possible values

for i = 1 to f do

Set the contents of N_i to D_i, where D_i is all instances in N that match F_i

Call BuildTree(N_i)

end for

end if

(Guo et al. 2019)

Pseudo-code algorithm of logistic regression: (Pseudocode of Logistic Regression, n.d.)

Input: Training data

1. For i←1 to k
2. For each training data instance d_i:
3. Set the target value for the regression to
   $z_i \leftarrow \frac{y_j - P(1 \mid d_j)}{[P(1 \mid d_j) . (1 - P(1 \mid d_j))]}$
4. nitialize the weight of instance d_j to P $(1 \mid d_j)$. $(1 - P (1 \mid d_j)$
5. finalize a f(j) to the data with class value (z_j) & weights (wj)

   Classification Label Decision
6. Assign (class label:1) if P $(1|d_j) > 0.5$, otherwise (class label: 2)