BRITISH AIRWAYS
Insights & Analysis

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Client & Scope of Analysis

- **Client:** British Airways Reviews Dataset
- **Data Source:** Kaggle

Prediction Question:

Can we predict which variables are likely to yield higher passenger satisfaction scores based on historical ratings data?

Key Objectives:

- Identify the Best Model for Making Predictions
- Identify Key Satisfaction Drivers
- Uncover Hidden Patterns and Insights
- Enhance Decision-Making and Strategic Planning

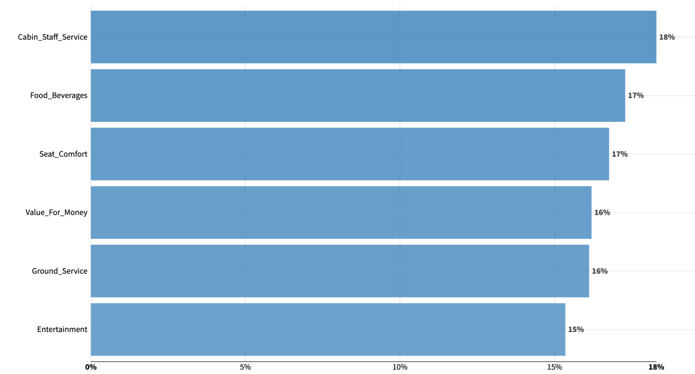
Our client for this project is British Airways, with data sourced from the Kaggle.

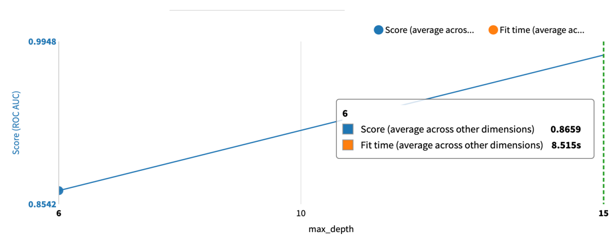
The central question I aimed to answer with this analysis was: 'Can we predict which variables are likely to yield higher passenger satisfaction scores based on historical ratings data?'.

With this analysis I wanted to uncover deeper insights and patterns that are not readily visible through basic data review, by leveraging advanced predictive modeling techniques, including Random Forest, Decision Tree, and **Extreme Gradient Boosting**.

My goal is to provide British Airways with actionable insights that can significantly enhance their customer satisfaction strategies. This analysis should not only help British Airways in identifying key areas of improvement but also help them in making informed decisions in the future that align with passenger expectations.

Random Forest (RF)





Accuracy	0.9286
Precision	0.8945
Recall	0.8719
F1-score	0.8830

	Predicted 1	Predicted 0	Total
Actually 1	5417	796	6213
Actually 0	639	13236	13875
Total	6056	14032	20088

The first model I created was the Random Forest. Which is a method that utilizes multiple decision trees to make predictions.

Looking at the hyperparameters, I found that as the maximum depth of the decision trees increases from 6 to 10. Which means that the model's ability to distinguish between satisfied and unsatisfied passengers improves significantly. However, while deeper trees enhance the model's accuracy, they also require more time to compute.

The Feature importance highlights that Cabin Staff Service, Food and Beverages, and Seat Comfort are the top predictors of satisfaction. This suggests that improvements in these areas could lead to higher overall passenger satisfaction.

Looking at the performance metrics, the model shows an accuracy rate of 93%. This high level of accuracy ensures that the predictions made by the model are reliable and can be trusted to reflect true passenger satisfaction levels accurately.

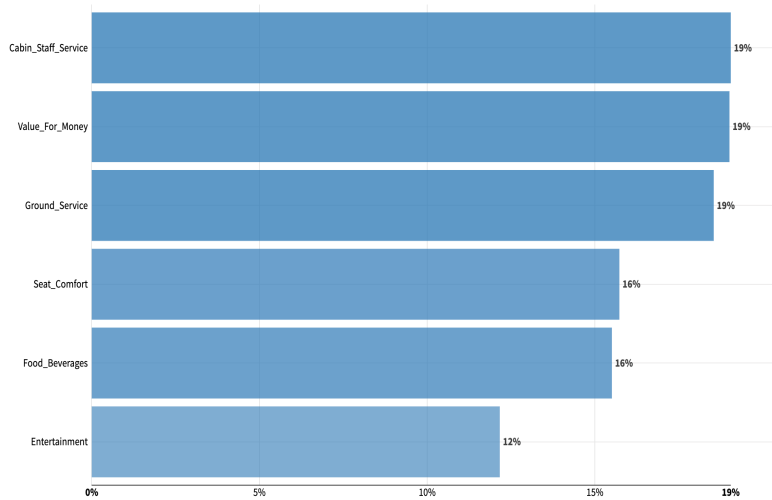
Moving on to precision — at 89%, this metric tells us that when our model predicts that passengers are satisfied, it is correct 89% of the time.

The recall rate of 87% demonstrates the model's ability to identify most of the actually satisfied passengers effectively.

Lastly, the F1-score, which stands at 88%, highlights a well-balanced relationship between precision and recall. This means that the model is consistent and reliable, and doesn’t favor one aspect of prediction over the other.

In the confusion matrix, we can observe 5,417 true positives, where the model correctly predicts satisfaction.
However, there are still areas for improvement, as indicated by 639 false positives and 796 false negatives, which shows us that there are potential misclassifications that we should aim to minimize.

XGBoost (Extreme Gradient Boosting)



Accuracy	0.8544
Precision	0.7334
Recall	0.8318
F1-score	0.7795

	Predicted 1	Predicted 0	Total
Actually 1	5168	1045	6213
Actually 0	1879	11996	13875
Total	7047	13041	20088

Moving forward, we have our second model, the XGBoost, or Extreme Gradient Boosting.

Feature Importance Insights:

•In the XGBoost model, we see that Cabin Staff Service, Value for Money, and Ground Service each hold an equal importance of 19%. This uniform distribution shows us the balanced impact these factors have on passenger satisfaction. Both the quality of service and the perception of value seem to be critical components.

On the flip side, features like In-flight Entertainment, Food and Beverages, and Seat Comfort, show slightly less influence, each contributing 12% to 16%.

Performance Metrics:

•The model has an accuracy of 85.44%, indicating strong overall performance in correctly identifying both satisfied and unsatisfied passengers.

•With a precision of 73.34%,.

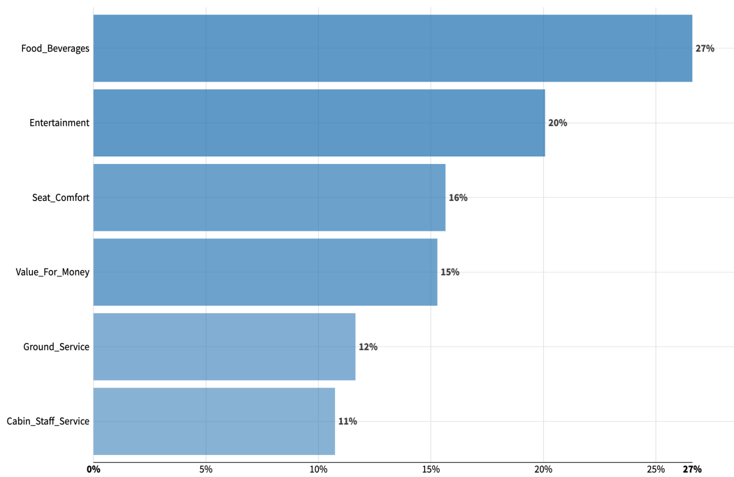
The recall rate stands at 83.18%,.

•and the F1-score of 77.95%.

Looking at the Confusion Matrix, We can observe 5,168 true positives, where passengers were correctly identified as satisfied. But there are 1,879 false positives, which are instances where passengers were incorrectly labeled as satisfied, and 1,045 false negatives where the model missed identifying satisfied passengers. The model also correctly identified 11,996 true negatives.

In essence, the XGBoost model does show good performance.

Decision Tree (DT)



Accuracy	0.6340
Precision	0.4438
Recall	0.7241
F1-score	0.5503

	Predicted 1	Predicted 0	Total
Actually 1	4499	1714	6213
Actually 0	5639	8236	13875
Total	10138	9950	20088

The third model in my analysis is the Decision Tree. This is straight-forward, it constructs a tree-like graph of decisions, making it one of the most transparent models used in predictive analytics.

Looking at the model’s feature importance, 'Food and Beverages’ is the most significant predictor of passenger satisfaction, accounting for 27% of the model's predictive power. 'In-flight Entertainment' also stands out with a 20% influence, which is much more than in the Random Forest and XGBoost models. An interesting observation here is that 'Cabin Staff Service' and 'Ground Service', which were highly influential in the other models, are given less priority here. Which could mean there is a potential difference in how the Decision Tree model perceives the impact of service quality compared to tangible amenities.

Performance Metrics:

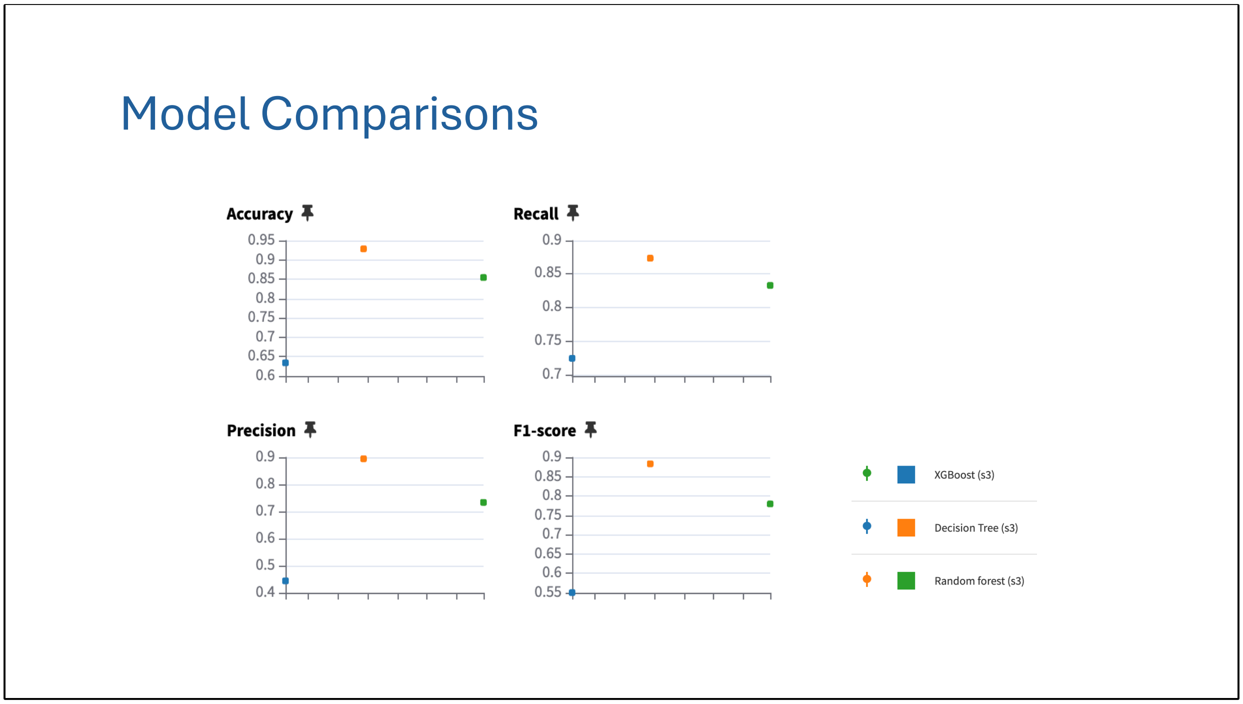
•The Decision Tree model shows an accuracy of 63.40%, which is significantly lower compared to the other models.

•Precision is at 44.38%, indicating that less than half of the passengers identified as satisfied by this model are actually satisfied. Which could suggest a high rate of false positives.

•The recall rate is relatively better at 72.41%, showing the model's reasonable capability in identifying who is satisfied
•The F1-score is low at 55.03%, it reflects a poor balance between precision and recall

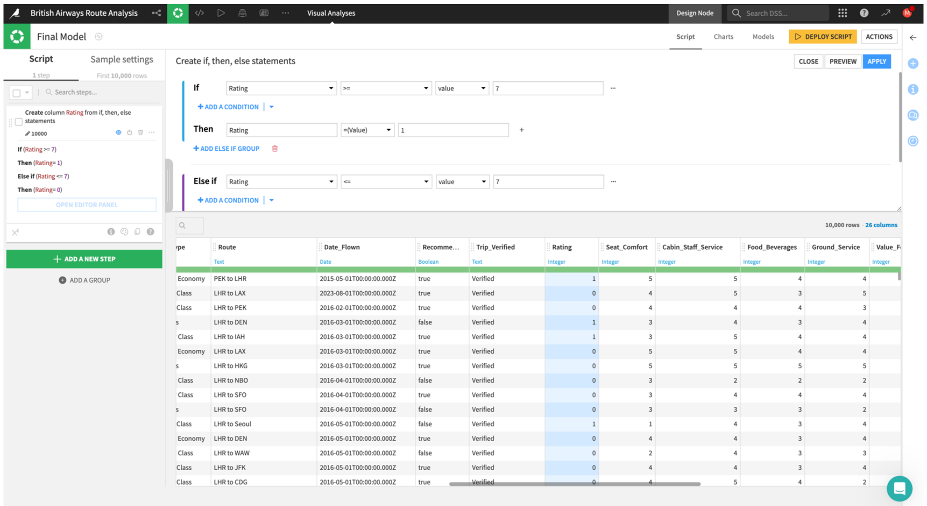
•**Confusion Matrix Overview**
•We observed 4,499 true positives.
•However, the model also misidentified 5,639 passengers as satisfied—these false positives, along with 1,714 false negatives, is very high.
•The true negatives were 8,236, showing that the model can correctly identify a number of unsatisfied passengers.

•So in summary, while the Decision Tree model does offer straightforward insights into how decisions are made, its lower performance metrics make it a less suitable model.



Moving onto model comparisons – The **Random Forest model** emerges as the superior choice for British Airways. It not only achieves the highest ROC AUC score of 0.984, demonstrating exceptional capability in distinguishing between satisfied and unsatisfied passengers, but also boasts the highest F1-score of 88.3%. This score is crucial as it indicates a strong balance between precision and recall—essential attributes for a reliable prediction model.

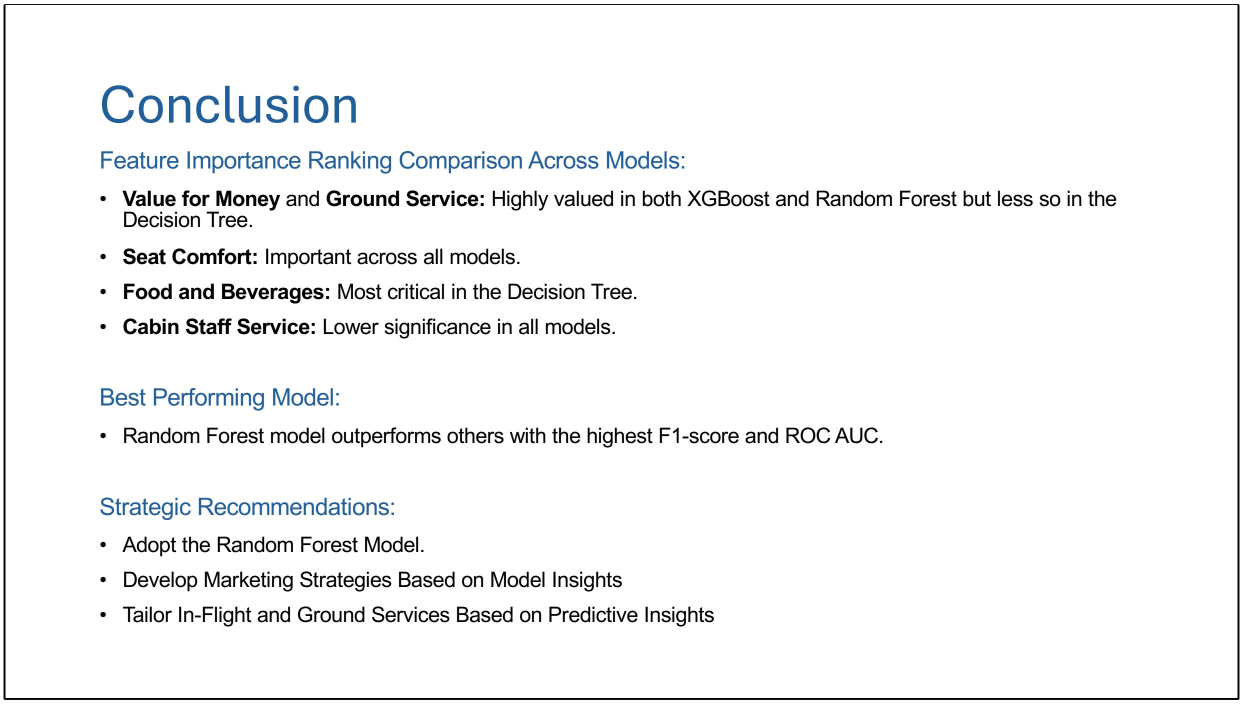
Limitations in Model



While working on this project a limitation I faced was with the target variable 'Rating'. The original "Rating" variable consisted of values from 1 to 10, which automatically set up a multiclass classification problem. In multiclass classification, the distance between the actual and predicted classes isn't considered. A near-miss is treated the same as a far miss, which can misrepresent the model's predictive accuracy.

In order to fix this and achieve better performing models, I decided to convert the 'Ratings' variable into a binary classification. So now Ratings greater than or equal to 7 were encoded as 1 (Positive/Satisfied). Ratings less than 7 were encoded as 0 (Negative/Not Satisfied).

This transformation simplified the problem into binary classification, making it more straightforward to predict and interpret the outcomes as either satisfied or not satisfied.



As I conclude our analysis comparing the XGBoost, Decision Tree, and Random Forest models. I think its important to highlight some of the following information.

Key Takeaways:

1.Feature Importance Analysis:

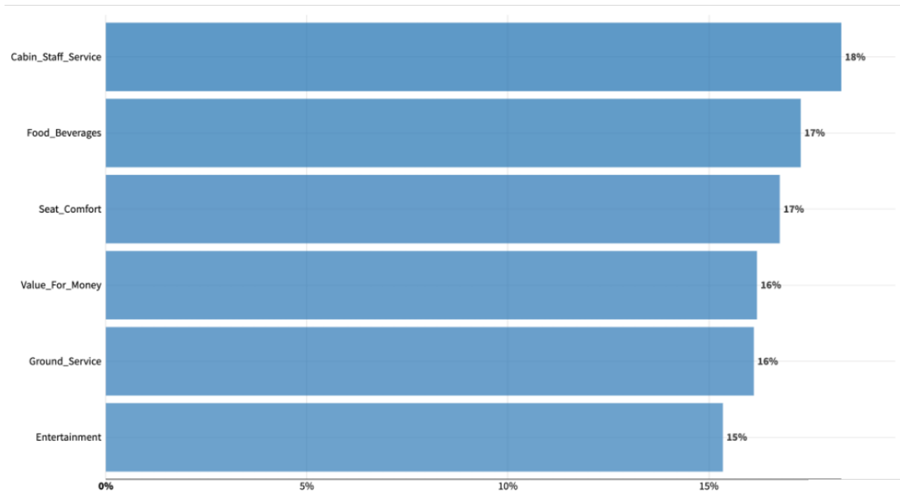
1. **Value for Money and Ground Service**: were significantly valued in both the XGBoost and Random Forest models, slightly less so in the Decision Tree.
2. **Seat Comfort**: was consistently important across all models, which highlights its universal impact on passenger satisfaction.
3. **Food and Beverages**: appeared to be the most critical in the Decision Tree, indicating unique sensitivities in this model.
4. **Cabin Staff Service**: Interestingly, this feature showed lower significance across all models, which was unexpected.

5. The best model was The Random Forest model, because not only outperformed the others with the highest F1-score and ROC AUC but also demonstrated reliability in its predictive accuracy.

Some strategic recommendations would be to
-Adopt the Random Forest Model: Given its superior performance, it is recommended that British Airways implement this model to enhance predictive accuracy in passenger satisfaction initiatives
-Utilize detailed insights from the Random Forest model to refine service offerings, particularly focusing on highly ranked features such as seat comfort and value for money.
•Lastly, develop targeted marketing campaigns that accentuate the improved services most valued by passengers, leveraging the predictive power of the Random Forest model to attract and retain customers.

Appendix

- Dataiku Wiki Article:
- https://dss-f285e3fa-c773e3a3-dku.us-east-1.app.dataiku.io/projects/BRITISHAIRWAYSROUTEANALYSIS/wiki/8/Analyzing%20Passenger%20Satisfaction%20for%20British%20Airways%20Using%20Predictive%20Modeling



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Random Forest Feature Importance & Confusion Matrix

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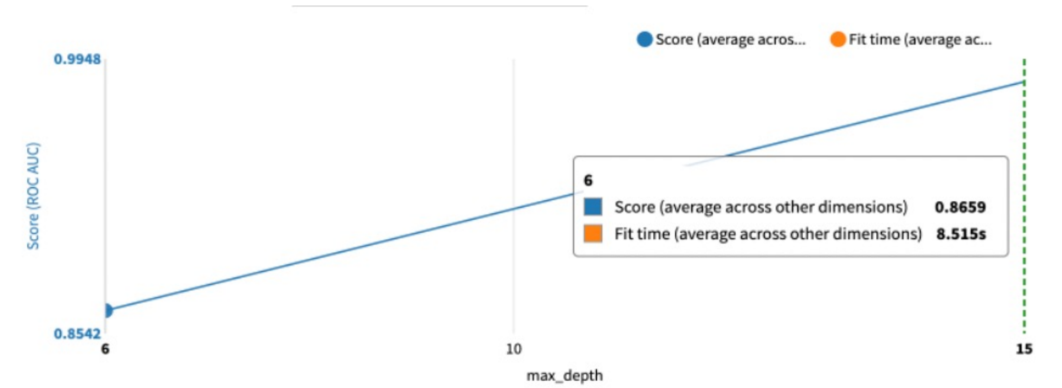
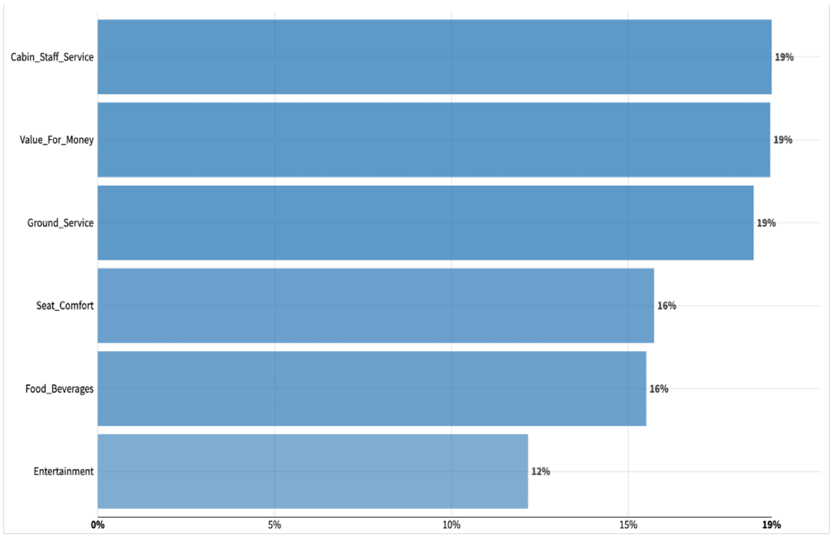


Random Forest Hyperparameters & Metric Details



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Accuracy	**0.8544**
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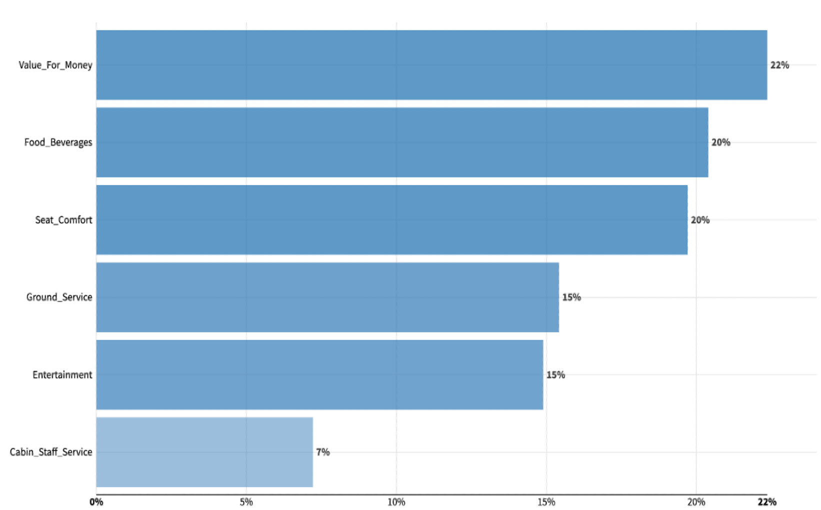
XGBoost Feature Importance, Metric Details & Confusion Matrix



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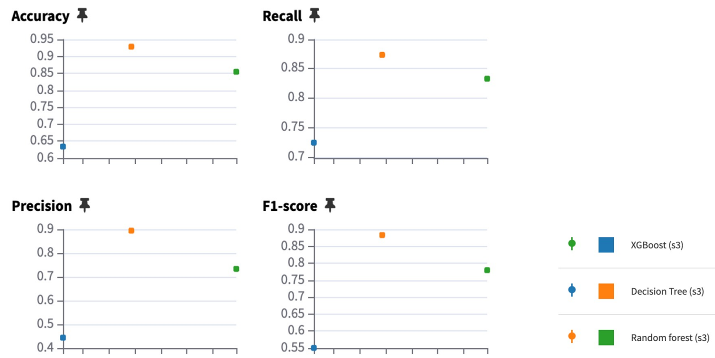
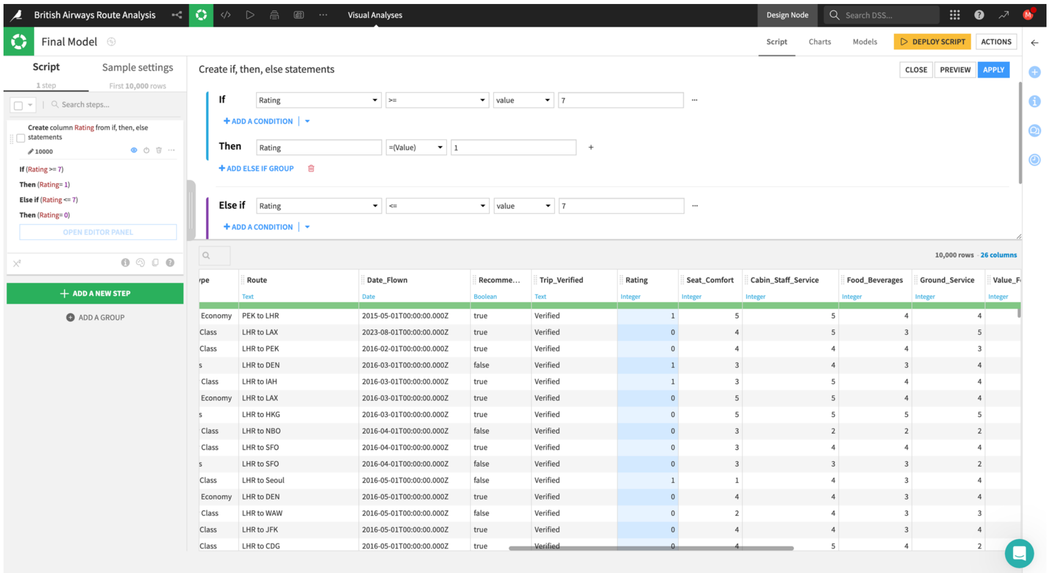
Decision Tree Feature Importance, Metric Details & Confusion Matrix



Model Comparison



IF/Else Statements – Model Limitations