Proceedings of the 3rd International Conference on Financial Technology and Business Analysis
DOI: 10.54254/2754-1169/2024.24033

A USA Airline Business Traveler Loyalty Model: Cost-Effective Approaches to Enhance Customer Retention

Luyun Zhang[1†], Muxi Chen[2*†], Yibin Li[3#], Mingze Gao[4#], Yanfu Zhang[5#], Changbin Feng[6#]

[1]Business School, The University of Edinburgh, Edinburgh, UK
[2]Questrom School of Business, Boston University, Boston, USA
[3]Rutgers Business School, Rutgers University-NB, Piscataway, USA
[4]College of Art & Science, University of Virginia, Charlottesville, USA
[5]School of Economics and Management, Xidian University, Xi 'an, China
[6]Department of Economic Management, North China Electric Power University, Baoding, China
**Corresponding Author. Email: chenmuxi@bu.edu*
[†]These authors contributed equally to this work and should be considered as co-first author.
[#]These authors contributed equally to this work and should be considered as co-second author.

Abstract: The airline industry remains highly competitive, making customer loyalty a crucial factor for maintaining profitability and ensuring long-term success. This research aims to uncover how airlines can strategically optimize their services to convert more customers, especially the business travelers that represent a significant revenue stream into loyal participants while minimizing costs. We are focusing on exploring the importance of class preferences and specific service features such as in-flight service quality that shape loyalty. The sample source for this study is derived from the U.S. Airline Passenger Satisfaction Survey. We employ a Decision Tree algorithm to construct a predictive model that assesses the loyalty of business-traveler customers to the airline. We found that airlines can enhance loyalty among business travelers by improving the ease of online booking and boarding service, and customizing services based on ages and flight distance tiers.

Keywords: Machine Learning, Decision Tree Model, Prediction, Airline Loyalty, Business Travelers

1. Introduction

As the airline industry continues to recover from COVID-19, it remains highly competitive, and customer loyalty has still been a vital component in bringing about long-term success and ensuring profitability in the business world, particularly for the airline industry that values changing customer expectations a lot [1]. Loyalty programs, referring to institutionalized incentive systems that attempt to enhance customers' perceived values, emotional engagement, brand loyalty, and willingness to pay [2], are widely utilized by airlines to retain frequent business travelers, but not all participate, and the processes for how to conduct this are not well-examined [3]. While existing research highlights the benefits of loyalty programs and their impact on customer retention, areas of improvement in understanding why some business travelers choose or choose not to engage have yet been presented [4]. In addition, the insights into how airlines can optimize service quality across cabin classes to enhance loyalty while maintaining cost efficiency are limited [5]. Business travelers and leisure

DOI: 10.54254/2754-1169/2024.24033

travelers are driven by different factors, thus it is reasonable to segment customer groups based on the type of travel in this paper. As previous research stated the airline loyalty of business is not only shaped by service quality and perceived value but also by rewards and personalized experiences, this paper seeks to uncover the key factors that impacting business travelers' loyalty and their engagement with loyalty programs through decision tree modeling, enabling airlines to draw up strategies to enhance profitability and retain customer base in a competitive market.

2. Literature review

Service quality has consistently been identified as a primary driver of customer satisfaction in the airline industry. The relationship between service quality and loyalty is well-documented, with numerous studies emphasizing that enhanced service quality leads to higher levels of satisfaction [6], and consequently, stronger loyalty [7]. For instance, in-flight service quality, including factors such as comfort, staff behavior, and on-board amenities, has been shown to significantly influence customer satisfaction and loyalty, especially among business travelers [8].

Loyalty programs, which are designed to bring about a sense of loyalty by rewarding repeat customers by offering points, upgrades, and other benefits [5], have been viewed as an essential and effective tool by airlines to retain customers, especially among those business travelers who fly frequently [9]. Research reveals the secret behind, loyalty tactics are effective among business travelers as they value both the utilitarian and symbolic benefits these programs offered [10]. And the success of these programs often depends on how customers perceive the value and the rewards, which varies significantly based on their level of engagement and how frequent they travel [11].

oreover, the effectiveness of loyalty programs depends on the level of customer involvement and the perceived value of the rewards offered. Higher levels of loyalty among customers who actively participate in loyalty programs tend to link to their satisfaction with the benefits provided [5]. However, the challenge for airlines lies in tailoring these programs to meet the specific needs and preferences of business travelers, who may have different expectations than leisure travelers [4]. Particularly, many business travelers often seek programs that offer not only rewards, but also convenience, flexibility, and recognition of their frequent travel that accents the importance of personalized service delivery [12].

However, the relationship between satisfaction of service quality and loyalty is not straightforward. As Dolnicar et al. [13] argue, satisfaction alone may not always be a direct predictor of loyalty, particularly in a market where customers have numerous alternatives offering tailored services to specific demand. This complexity is illustrated by the evolving expectations of modern travelers, who have increasingly valued personalized experiences and the seamless integration of digital services throughout their travel journey [14]. Therefore, while service quality is necessary for ensuring customer satisfaction, it may not be sufficient for securing customer loyalty, particularly among business travelers who may prioritize other factors such as convenience and flight-frequency rewards.

In order to fully make use of the loyalty program, it is very crucial for airlines to understand whether and how these programs incorporate into a broader strategy of customer segmentation and service differentiation. The segmentation of customers based on their travel purpose is another important consideration for airlines aiming to enhance loyalty. Compared to leisure travelers, business travelers as a distinct segment often have different expectations and requirements, especially those concerning class preferences and in-flight service features [4]. Chonsalasin et al. [7] in their research highlights that business travelers place a higher emphasis on convenience, comfort, and personalized services, and these features are often associated with premium classes. Furthermore, to satisfy these demands, the integration of digital tools such as mobile apps which are created for the seamless booking and personalized airline travel experiences has become more and more important as well [15].

DOI: 10.54254/2754-1169/2024.24033

Additionally, the incremental significance of sustainability and corporate social responsibility (CSR) plays a notable role in affecting customer loyalty [1]. Recent studies suggest that travelers, including business travelers, are becoming more aware of the environmental impact of their travel choices, and airlines that actively engage in sustainable practices may enhance their loyalty base [16]. And this trend indicates a potential shift in the factors influencing loyalty, where ethical considerations might begin to play a larger role alongside traditional service quality and rewards.

In summary, though service quality may remain a cornerstone of customer satisfaction, its direct impact on loyalty is nuanced and often influenced by a myriad of factors, including personalization, digital engagement, and sustainability. Airlines aiming to enhance loyalty among business travelers must, therefore, it is essential for them to adopt a holistic approach that not only maintains high service standards but also innovates in areas such as loyalty programs, digital services, and sustainability practices.

Therefore, we decided to outline the significant features that influence travelers' airline loyalty the most via the decision tree model, thereby airline companies will understand which dimensions they should prioritize and invest the most to improve customer loyalty cost-efficiently.

3. Methods

3.1. Data sampling

The dataset we utilized is derived from the U.S. Airline Passenger Satisfaction Survey, which provides true portrayal of traveler experiences and preferences across various airlines. The initial version of this dataset comprised 129,487 cases, with 50.7% female travelers and 49.3% male travelers. The majority of passengers' age is between 20 and 60, with a median age of around 39. The medium flight distance is around 800 miles and more travelers take short or medium-haul flights [17]. After undergoing a rigorous process of data cleansing and balancing, we got a final dataset which included 34,046 samples of business travelers and 294 samples of personal travelers. We then conducted a balancing process for loyal and disloyal customers to ensure equitability within each segment, which was particularly important in alleviating potential biases in the model.

Table 1: Variables of the decision tree model

Field name	**Description**	**Number of Null examples**
Gender	Gender of the passengers (Female, Male)	0
Age	The actual age of the passengers	0
Class	Travel class in the plane of the passengers (Business, Eco, Eco Plus)	0
Flight Distance	The flight distance of this journey	0
Inflight wifi service	Satisfaction level of the inflight wifi service (0: Not Applicable; 1-5)	0
Departure/Arrival time convenient	Satisfaction level of Departure/Arrival time convenient	0
Ease of Online booking	Satisfaction level of online booking	0
Gate location	Satisfaction level of Gate location	0
Food and drink	Satisfaction level of Food and drink	0
Online boarding	Satisfaction level of online boarding	0

Table 1: (continued)

Seat comfort	Satisfaction level of Seat comfort	0
Inflight entertainment	Satisfaction level of inflight entertainment	0
On-board service	Satisfaction level of On-board service	0
Leg room service	Satisfaction level of Leg room service	0
Baggage handling	Satisfaction level of baggage handling	0
Check-in service	Satisfaction level of Check-in service	0
Inflight service	Satisfaction level of inflight service	0
Cleanliness	Satisfaction level of Cleanliness	0
Departure Delay in Minutes	Minutes delayed when departure	0
Customer Type (target variable)	The type of customer (loyal customer or disloyal customer)	0

After employing the above segmentation approach to build separate decision tree models for business travelers and personal travelers, we split the dataset randomly into training and testing samples for each segment. More specifically, about 70% of the cases were allocated for model training, while the remaining 30% were reserved for testing the prediction model's performance. And after that, we developed a predictive model using the Decision Tree algorithm in order to accurately forecast the likelihood of travelers engaging in an airline loyalty program. And by analyzing this model, we are going to quest customers' various attributes, including different crucial elements and customer satisfaction level.

3.2. Decision tree model construction

The target variable for the decision tree model is the customer type, which classifies customers as either loyal or disloyal. The predictors, selected based on their potential influence on customer loyalty, present in table 1.

Our initial decision tree model was built using the DecisionTreeClassifier with the criterion set to "gini." However, to address potential overfitting, we employed a series of model improvement techniques. First, pre-pruning was applied by setting hyperparameters, including a maximum depth of 12, a maximum of 40 leaf nodes, and a varying number of minimum samples per leaf (ranging from 1 to 10). And the performance of this model was evaluated using accuracy, recall, precision, and F1 scores.

Despite these improvements, further refinement was deemed necessary, leading to the application of post-pruning techniques. Before implementing post-pruning, a cost-complexity analysis was conducted to determine the optimal value of ccp_alpha. The final model was constructed using the DecisionTreeClassifier with ccp_alpha set to 5.231962572327599e-05 and class weights assigned as {0: 0.15, 1: 0.85} to account for the class imbalance. The model's performance was then rigorously evaluated using the aforementioned metrics to ensure robust predictive accuracy and generalizability.

3.3. Model evaluation

3.3.1. Evaluation of business traveler segment model

For the business traveler segment, the performance of the decision tree models was evaluated via the following key metrics: accuracy, recall, precision, and F1 score on both the training and testing datasets. The initial version of the decision tree model, trained with default parameters, performed

DOI: 10.54254/2754-1169/2024.24033

perfect scores across all metrics on the training dataset, but this indicates significant overfitting. Although the model on the test dataset has an accuracy of 0.944 and an F1 score of 0.945, which performed reasonably well, the disparity between training and test results suggested that it might not generalize well to unseen data.

To tackle the overfitting problem, we decided to apply pre-pruning techniques through limiting the depth of the tree and controlling minimum samples per leaf and the number of leaf nodes. This pre-pruned model provided a more balanced performance between training and testing datasets, the generalization improved but at the same time there was a slight drop occurred in accuracy and recall. This new model's test accuracy is 0.906 and F1 score is 0.905.

Then we further refined the model by post-pruning, utilizing cost-complexity pruning to optimize model performance while controlling for complexity. We got a substantial improvement, on the test dataset the post-pruned model achieved an accuracy of 0.939 and an F1 score of 0.941. Therefore, this model has become a reliable tool to predict business travelers' willingness to become members of loyalty programs, as it offers the best balance among accuracy, recall, and precision.

Table 2: Performance of business traveler segment decision tree models

Performance of Business Traveler Segment Model								
	Train				**Test**			
Model	**Accuracy**	**Recall**	**Precision**	**F1**	**Accuracy**	**Recall**	**Precision**	**F1**
Decision Tree sklearn	1.0000	1.0000	1.0000	1.0000	0.9440	0.9453	0.9438	0.9446
Decision Tree (Pre-Pruning)	0.9082	0.8899	0.9231	0.9062	0.9060	0.8875	0.9233	0.9050
Decision Tree (Post-Pruning)	0.9684	0.9992	0.9410	0.9692	0.9390	0.9707	0.9138	0.9414

3.3.2. Evaluation of personal traveler segment model

In contrast, the performance on the decision tree models for the personal traveler segment presented significant challenges. Regarding the initial model, the perfect scores on the training data set reflect severe overfitting. However, the test dataset performance was notably poor, with an accuracy of 0.4719 and an F1 score of 0.4835. These metrics revealed high false negatives and false positives, indicating the model's poor ability to correctly identify potential loyal customers.

The application of pre-pruning techniques resulted in a slight improvement in overfitting and prediction accuracy. Yet, the model still struggled with generalization as a testing accuracy of 0.5169 and F1 score of 0.6055.

Post-pruning was applied to further refine the model, but the results remained suboptimal. The post-pruned model achieved an accuracy of 0.4719 and an F1 score of 0.6412 on the test dataset. Although the F1 score was improved, the overall performance revealed an inadequate capacity in capturing loyal leisure customers accurately.

DOI: 10.54254/2754-1169/2024.24033

Table 3: Performance of personal traveler (leisure) segment decision tree models

Performance of Business Traveler Segment Model								
	Train				Test			
Model	**Accuracy**	**Recall**	**Precision**	**F1**	**Accuracy**	**Recall**	**Precision**	**F1**
Decision Tree sklearn	1.0000	1.0000	1.0000	1.0000	0.4719	0.5238	0.4490	0.4835
Decision Tree (Pre-Pruning)	0.6683	0.9048	0.6209	0.7364	0.5169	0.7857	0.4925	0.6055
Decision Tree (Post-Pruning)	0.5122	1.0000	0.5122	0.6774	0.4719	1.0000	0.4719	0.6412

And considering the accuracy and F1 scores in the personal traveler segment are persistently low, it is evident that the high false negative and false positive rates make the model unsuitable for practical application, particularly in detecting potential loyal customers. The challenges observed in the personal traveler segment likely stem from insufficient or imbalanced data, which hinders the model's ability to learn meaningful patterns. As a result, we have decided to abandon the personal traveler segment model and focus on the business traveler segment.

4. Results

By employing the post-pruning decision tree, we have been able to define several significant attributes that influence customer loyalty among the business-traveler segment. The algorithm's analysis revealed that *Age* and *Flight Distance* are the most powerful predictors in determining the likelihood of a business traveler becoming a loyal customer, with an importance score of 0.214602.

Table 4: The importance of features

Feature	Importance	Feature	Importance
Age	0.214602	Baggage handling	0.019851
Flight Distance	0.141626	Food and drink	0.01932
Departure/Arrival time convenient	0.121166	Inflight service	0.018495
Ease of Online booking	0.092073	Cleanliness	0.017781
Gate location	0.063554	On-board service	0.017569
Online boarding	0.062949	Checkin service	0.010435
Inflight entertainment	0.056617	Leg room service	0.009147
Class_Eco	0.044138	Gender_Male	0.00608
Inflight wifi service	0.039258	Class_Eco Plus	0.004271
Seat comfort	0.038136	Departure Delay in Minutes	0.002933

This suggests that the propensity for loyalty varies across different age demographics. For instance, younger business travelers may prioritize technological conveniences and modern amenities [18], whereas older travelers might place greater emphasis on comfort, reliability, and the availability of premium services, all of which contribute to their loyalty decisions [19]. Flight distance emerged as a significant predictor of loyalty as well, its importance score is 0.1416. Business travelers who frequently undertake long-haul flights are likely to find substantial value in loyalty programs that offer benefits such as upgrades, access to lounges, and other premium services that enhance the overall travel experience [20].

In addition, other attributes also play vital roles, such as *Departure/Arrival Time Convenience* and *Ease of Online Booking*. These factors collectively shape how business travelers, who often have tight schedules, make decisions when they are considering whether to participate in an airline's loyalty program. For instance, the importance score of Departure/Arrival Time Convenience is 0.1212. For them, the ability to choose flights that align with their professional commitments can significantly enhance the travel experience. Also, ease of Online Booking contains the importance of 0.0921), which indicates that a streamlined, user-friendly online booking process not only saves time but also enhances the overall customer experience, making it more likely that a traveler will continue to choose the same airline.

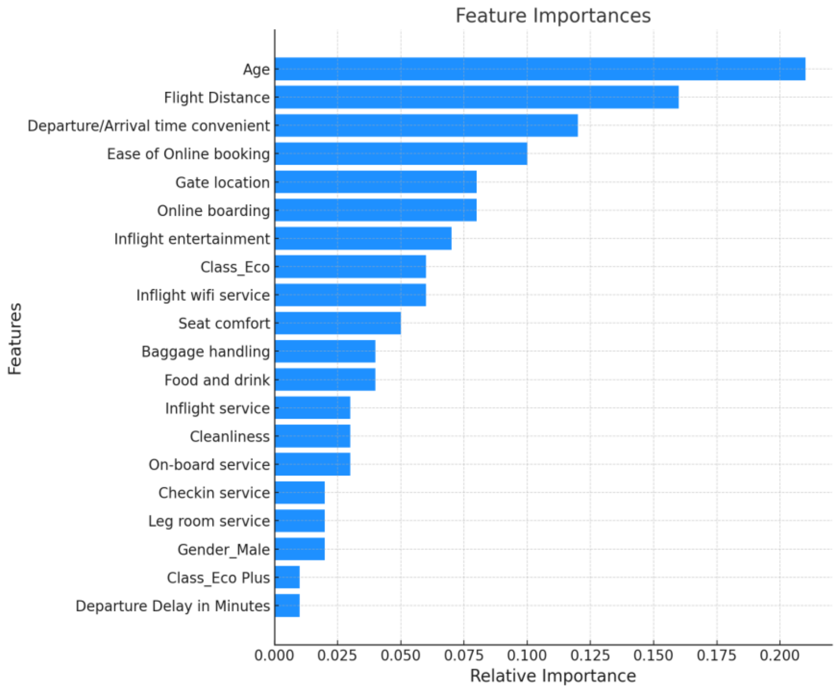

Figure 1: Feature importance of each predictors in the decision tree model

5. Discussion

5.1. Contribution

This study contributes to the previous research on customer loyalty in the airline industry by providing a data-driven analysis of the factors that influence business travelers' decisions to engage with loyalty programs. The construction of a post-pruning decision tree model offers a transparent and interpretable approach [21] to understanding these dynamics [22]. The identification of key attributes that drive loyalty adds to the body of knowledge by highlighting the specific areas where airlines can focus their efforts on enhancing customer satisfaction and retention.

5.2. Implications

The insights derived from the decision tree model have several practical implications for airline companies seeking to optimize their loyalty programs and customer retention strategies. Airlines should consider segmenting their loyalty programs to cater specifically to different age groups and frequent long-haul travelers. Regarding age segmentation, the airline may include differentiated

DOI: 10.54254/2754-1169/2024.24033

services according to age range. i.e. offer discounts to young adults on flights; offer professionals occasional access to lounges; and include wellness options in seniors' travel packages, such as spa treatments or health-related workshops [23]. For flight distance segmentation, airlines may implement a tiered points system within frequent-flyer programmes that rewards travelers more for long-haul flights, potentially offering double or triple points [24].

Besides, the research highlights the need for airlines to invest in improving customer experience by ensuring that business travelers have access to convenient flight schedules and efficient online booking platforms, which thereby increasing the likelihood of loyalty. And when promoting loyalty programmes, airlines should strategically underscore their advantages in these selling points.

5.3. Limitation and outlook

The generalizability of our findings is constrained by the regional specificity of the dataset. The data used in this study were derived from U.S. airline passenger satisfaction surveys, which may reflect the preferences and behaviors of travelers within the United States. As a result, it may be challenging to apply these results universally across different regions where cultural, economic, and operational differences could lead to varying factors influencing customer loyalty [25]. Thus, we should pay extra attention when we extend these findings to other geographical contexts.

Moreover, decision trees are known as they cannot generalize to variations not seen in the training set [26]. Therefore, future research should consider using ensemble methods or other advanced machine learning techniques to improve the reliability of the findings.

Acknowledgement

Luyun Zhang and Muxi Chen contributed equally to this work and should be considered co-first authors.

Yibin Li, Mingze Gao, Yanfu Zhang, Changbin Feng contributed equally to this work and should be considered co-second authors.

References

[1] Duong, H. M., Pham, D. H., Ho, T. N. H., Nguyen, H. Q., & Le, N. D. (2023). Perception of crisis management, service quality, and loyalty programs on airline travel intention: What roles do fear of COVID-19 and risk attitude play? Sustainability, 15(18), 13753. https://doi.org/10.3390/su151813753
[2] Su, Yu, Craig Lee, and Brent Lovelock. 2023. "Airline and Hotel Loyalty Programme Diversity and Choice: Effects of Personality, Cultural, and Socio-Demographic Factors." Journal of Travel & Tourism Marketing 40 (8): 653–77. doi:10.1080/10548408.2023.2285926.
[3] Chen, Yanyan, Timo Mandler, and Lars Meyer-Waarden. "Three Decades of Research on Loyalty Programs: A Literature Review and Future Research Agenda." Journal of Business Research 124 (2021): 179-197. https://doi.org/10.1016/j.jbusres.2020.11.057.
[4] Wang, E.ST., Chen, L.SL. & Chen, I.F. The antecedents and influences of airline loyalty programs: the moderating role of involvement. Serv Bus 9, 257–280 (2015). https://doi.org/10.1007/s11628-013-0226-6
[5] An, M., Noh, Y. Airline customer satisfaction and loyalty: impact of in-flight service quality. Serv Bus 3, 293–307 (2009). https://doi.org/10.1007/s11628-009-0068-4
[6] Limberger, Pablo Flôres, Lucimari Acosta Pereira, and Tércio Pereira. "The impact of customer involvement in airline loyalty programs: a multigroup analysis." Tourism & Management Studies 17, no. 3 (2021): 37-49.
[7] Singh, Balgopal. "Predicting airline passengers' loyalty using artificial neural network theory." Journal of air transport management 94 (2021): 102080.
[8] Chonsalasin, Dissakoon, Sajjakaj Jomnonkwao, Kattreeya Chanpariyavatevong, Wimon Laphrom, and Vatanavongs Ratanavaraha. "Modeling of airline passenger loyalty: A comparison of leisure and business travelers." Research in Transportation Business & Management 43 (2022): 100735.
[9] Pascual, Manuel E., and Lisa Nicole Cain. "Loyalty programs: The vital safety feature for airlines to survive COVID-19." International Hospitality Review 36, no. 1 (2022): 124-130.

DOI: 10.54254/2754-1169/2024.24033

[10] Gilbert, D. C. "Relationship marketing and airline loyalty schemes." Tourism management 17, no. 8 (1996): 575-582.
[11] Omar, R., & Harun, A. (2023). Airline satisfaction and loyalty: Assessing the influence of personality, trust and service quality. Journal of Air Transport Management, 104, 102324. https://doi.org/10.1016/j.jairtraman.2023.102324
[12] Han, H., & Hyun, S. S. (2010). Airline customer satisfaction and loyalty: Impact of in-flight service quality. Journal of Innovation and Entrepreneurship, 7(3), 215-230. https://doi.org/10.1007/s11628-009-0068-4
[13] Dolnicar, Sara, Klaus Grabler, Bettina Grün, and Anna Kulnig. "Key drivers of airline loyalty." Tourism Management 32, no. 5 (2011): 1020-1026.
[14] Gustafsson, A. (2019). The Digitalization of the Airline Industry: Opportunities and Challenges. Journal of Air Transport Management, 80, 101-113. https://doi.org/10.1016/j.jairtraman.2019.101113
[15] Liu, Y., & Lee, J. (2013). The antecedents and influences of airline loyalty programs: The moderating role of involvement. Journal of Innovation and Entrepreneurship, 8(1), 22-35. https://doi.org/10.1007/s11628-013-0226-6
[16] Assaf, A. G., Tsionas, M., & Josiassen, A. (2023). The effect of airline passengers' satisfaction on loyalty: Do region and airline carrier matter? A meta-analysis study. Journal of Hospitality and Tourism Management.
[17] Wilkerson, J. T., Mark Z. Jacobson, Andrew Malwitz, Sathya Balasubramanian, R. Wayson, G. Fleming, A. D. Naiman, and S. K. Lele. "Analysis of emission data from global commercial aviation: 2004 and 2006." Atmospheric Chemistry and Physics 10, no. 13 (2010): 6391-6408.
[18] Richards, Greg, and Julie Wilson. New horizons in independent youth and student travel: Summary report. International Student Travel Confederation (ISTC), 2003.
[19] Zielińska-Szczepkowska, Joanna. "Travel Behavior of the Elderly and Quality-of-Life." In Handbook of Tourism and Quality-of-Life Research II: Enhancing the Lives of Tourists, Residents of Host Communities and Service Providers, pp. 153-165. Cham: Springer International Publishing, 2023.
[20] Goh, Kevin, and Mark Uncles. "The benefits of airline global alliances: an empirical assessment of the perceptions of business travelers." Transportation Research Part A: Policy and Practice 37, no. 6 (2003): 479-497.
[21] Almuallim, Hussein. "An Efficient Algorithm for Optimal Pruning of Decision Trees." Artificial Intelligence 83, no. 2 (1996): 347-362. https://doi.org/10.1016/0004-3702(95)00060-7.
[22] Kotsiantis, Sotiris B. "Decision trees: a recent overview." Artificial Intelligence Review 39 (2013): 261-283.
[23] Skift.com, 2017. US Millennials Travel the Most but Gen Z is on the rise. [online] Available at: https://skift.com/2017/10/02/u-s-millennials-travel-the-most-but-gen-z-is-on-the-rise/ [Accessed 24 August 2019].
[24] Camilleri, Mark Anthony, and Mark Anthony Camilleri. The airline business. Springer International Publishing, 2018.
[25] Punel, Aymeric, Lama Al Hajj Hassan, and Alireza Ermagun. "Variations in airline passenger expectation of service quality across the globe." Tourism management 75 (2019): 491-508.
[26] Bengio, Yoshua, Olivier Delalleau, and Clarence Simard. "Decision trees do not generalize to new variations." Computational Intelligence 26, no. 4 (2010): 449-467.

Appendix

Appendix A. dataset source

Our dataset is found on Kaggle, and the website is: https://www.kaggle.com/datasets/teejmahal20/airline-passenger-satisfaction