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Evaluating the Effectiveness of Marketing Campaigns on Loyalty Program Engagement and Flight Bookings Across Key Demographics in Canada

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1. STATEMENT OF PURPOSE

Marketing campaigns drive the value of customer engagement and loyalty in the airline sector. In the increasingly competitive aviation sector, where passengers are becoming more accustomed to personalized travel experiences, today's loyalty programs have evolved into complex mechanisms that extend far beyond simply rewarding frequent flyers to drive bookings and foster brand advocacy. While acquisition costs continue to increase, retaining customers through loyalty solutions is a more sustainable way to grow the business.

The purpose of this study is to investigate how marketing campaign efforts influence two important loyalty metrics: engagement and bookings, by applying demographic segmentation. As behavioral data and demographic data become more accessible, airlines are in a unique position to use predictive analytics to create smarter and more effective campaigns.

Combining the process of exploratory data analysis, feature engineering, as well as developing predictive models on logistic regression and decision trees, this project discovers the trends of responsiveness based on a wide variety of demographic segments in Canada. By doing so, not only does it show the practical application of data science methods in the travel domain, but also provides actions that airlines can take to customize outreach, allocate resources optimally, and retain customer trust over the long term - an important factor for stimulating engagement and loyalty among customers in the airline industry. For this analysis, we used data from an airline loyalty program to investigate how marketing campaigns affect two measures of program success: program engagement (points accumulated and redeemed) and flight bookings. We concentrate particularly on the extent to which these results differ among the most important demographic groups in Canada.

Through combining exploratory data analysis, feature engineering, and predictive modeling with respect to logistic regression and decision tree, we are seeking commonalities among responsive customers to new marketing programs and putting forward actionable insights to businesses on customer segmentation and campaign strategy.

1.1 RELEVANCE OF THE PROJECT

Airline loyalty programs are strategic instruments to keep customers, and personalized marketing is key to engagement. Recent research shows that customers' behavior metrics like repeat visit rate and the redemption of vouchers/loyalty points can be enhanced using targeted campaigns (Dorotic et al., 2011). Knowing the fact that demographic sensitivity can boost marketing investments in a better way would be helpful to airlines. The importance of this project is as follows:

1. It uses predictive analytics to solve a real travel problem.

2. It is an example of how regression models can be used to assess engagement.

3. It provides a predictive marketing strategy using data insights into the behavior of the users and users' demographics.

Practically speaking, the results of this study directly inform airline marketers and customer experience departments. For example, identifying segments such as high-income, well-educated women in Ontario and British Columbia with the highest response potential helps marketers target more effectively and commit dollars where they will receive the greatest engagement.

In addition, predictive modeling techniques such as logistic regression can be integrated with CRM systems for automatic customer segmentation and customization of marketing messages on a real-time basis. This way you can keep all high-value customers, but also promote these customers with relevant and timely offers.

For the customer experience teams, these insights facilitate forward-thinking service design by customizing reward structures, flight perks, and loyalty benefits according to customer profiles. Airline competition is strong, and operation-based strategies are useful to convert the results for customer satisfaction and long-term loyalty. Strategies for retention and personalized marketing are key to engagement.

More recently, there is evidence that targeted promotions can be effective in influencing customer behavior with respect to both purchase propensity and purchase frequency (Dorotic et al., 2011). Despite a few exceptions where smaller carriers come out ahead, knowledge of where carriers should place their marketing bets can be beneficial in terms of marketing dollars.

This project is significant in the following respects:

1. It is applying predictive analytics to a problem in the travel industry.

2. It also validates the usefulness of regression models to predict engagement.

3. It uses data-driven insights from transactional and demographic data to drive marketing strategy.

1.2 GOALS OF THE PROJECT

The main objective of this study is to investigate the impact of marketing programs on customer engagement and flight bookings in a Canadian carrier loyalty program.

We start by studying customer engagement and flight activities using data from loyalty programs to reveal behaviors and patterns and detect trends. It then drills down into which buyer segments respond most to various marketing tactics (designs).

Next, we train predictive models, such as linear and logistic regression, to predict customer engagement (categorically) and the probability of future interaction as an average treatment effect, respectively, based on observable features. The goal of these models is to be trustworthy enough for airlines to utilize for automated segmentation of customers and to focus on high-value segments.

Lastly, applying the results from data exploration and modeling, we contribute data-driven marketing recommendations directed at maximizing marketing strategy, enhancing campaign targeting, and maximizing return on investment on primary demographic groups, levels, and flights flown from loyalty program records.

1. Let's segment the demographics most responsive to marketing.

2. Create predictive models to categorize the type of people who are engaged.

3. Make business suggestions to maximize marketing initiatives.

1.3 SCOPE OF THE PROJECT

This research project aims to evaluate how different types of marketing campaigns influence engagement with airline loyalty programs and the subsequent effect on flight bookings, with a particular focus on key demographic segments within Canada.

Boundaries:

- Analyze customer loyalty and flight data from Canadian customers.

- Segment customers by demographic attributes (province, gender, education, salary).

- Quantify loyalty engagement through metrics like:

o Total points accumulated

o Points redemption behavior

o Total flights over time

- Evaluate changes in loyalty and flight activity over time, suggesting responsiveness to marketing efforts.

- Conduct comparative analysis across segments to identify high-ROI demographics.

- Develop predictive indicators of engagement using statistical or machine learning models.

- International customer data

- Direct measurement of specific marketing message content

- Real-time campaign A/B testing

Key Deliverables:

- Summary statistics of engagement across demographic groups

- Visualizations and dashboards showing flight and loyalty trends

- Insights into which demographics are most responsive to loyalty campaigns

- Recommendations for targeted marketing strategies

2. BACKGROUND RESEARCH AND LITERATURE SEARCH

As data analytics and machine learning have advanced, loyalty marketing has evolved to more personalized campaigns based on customer behavior as well as their demographic.

Airline loyalty programs are no longer retention tools, but strategic instruments that drive revenue, customer satisfaction, and brand affinity. Reward programs enhance repeat purchase, especially when the reward offer matches customers' life needs and characteristics of different customer segments (Chen & Wu, 2008; Dare, 2006; Jang, 2007; Liu, 2007).

This is where segmentation tactics and personalized engagement are key to successful campaign design. Similarly, Dorotic et al. (2011) show that the impact of marketing promotions within loyalty programs differs between high- and low-income, age, and education, indicating that a uniform marketing strategy is not optimal.

Logistic regression is widely used as a basic technique in marketing analytics because it is easy to interpret and apply to a practical problem of classification (Verhoef & Donkers, 2001). While more sophisticated machine learning algorithms such as decision trees and neural networks have gained popularity, logistic regression is still heavily used in a marketing production environment (e.g., churn prediction, segmentation, targeting for campaigns).

Xie and Chen (2013) conducted a comprehensive literature review of loyalty program research in hospitality and also verified the trend of growing importance of analytics-driven campaign design and predictive modeling to enhance targeting precision. Together, these studies highlight the importance of utilizing both behavioral and demographic data for predicting engagement and targeting marketing resources in an efficient manner.

We build on these with our project, applying regression modeling, clustering, and inferential statistics to commercial airline data. In so doing, it adds to the emerging literature on the role of predictive analytics in loyalty program design and highlights the extent to which marketing effectiveness can be objectively assessed along various demographic dimensions, with the

development of data analytics technology enabling "new world order science" and an ability to run campaigns to individual customer behaviors.

Loyalty programs are vital for repeat purchases, particularly if they are related to the customer's profile (Liu, 2007). Dorotic et al. (2011) found that demographics, for instance, income or education, influence the success of a marketing action. Logistic regression is a key modeling method used for behavior prediction and is widely applied in marketing because of its interpretability (Verhoef & Donkers, 2001).

More advanced techniques like ensemble learning or neural networks are also promising; however, logistic regression still serves as a fundamental for engagement classification.

3. DESIGN AND DATA COLLECTION

The data in this study is sourced from the internal customer loyalty program database of a Canadian airline in 2018. As a primary source, it was a treasure trove of real-world data on not only customer interaction patterns, but also a thorough analysis of behavioral dynamics on airline loyalty programs. There were several dimensions in the data:

• Customer Characteristics: Such as sex, income, education, marital status, and location of residence (province).

• Flight Activity: A list of the monthly number of bookings, distance covered by flights, and number of trips taken.

• Loyalty Program - Points: Points accrued, points redeemed, and point balances over time.

• Program Membership: Information about dates of program enrollment, length of account tenure, and cancellation history.

With such variables, we follow recommendations of loyalty program analytics found in literature (Liu, 2007; Dorotic et al., 2011). The data was de-normalized by joining some tables together using a primary identifier (Loyalty Number) to help in building unified customer profiles. There was some pre-processing of the input data in accordance with good data quality principles (Provost & Fawcett, 2013), which included the deletion of partial completion records and records with NULL or zero salary, and normalization of dates to ensure temporal consistency. One hot-encoding approach was applied to categorical variables (gender, education, province) as is standard within machine learning preprocessing to enable algorithms to be compatible (Kuhn & Johnson, 2013). Care was also exercised to examine the distributions of the variables and to deal with potential anomalies and outliers.

Feature engineering was a key process in enriching the analytical power of the dataset. An engagement score, a customized composite variable, was developed to measure the intensity of the interaction between any individual customer and the loyalty program:

Engagement Score = (Points Collected) + (Total Flights * 100)

This expression has both transactional and behavioral dimensions of loyalty. Through a combination of total accrued loyalty points as well as flight frequency, the engagement score acts as a multi-dimensional proxy of customer value and engagement, consistent with ideas in customer lifetime value literature (Verhoef & Donkers, 2001).

The engagement score also played a dual role in the analysis: as a continuous variable for segmentation, and as a metric to form the binary classification. Cut-off was according to the median engagement score, dividing customers in high or low engagement. This classification method guaranteed the balance of the target distribution, which is necessary to maintain the integrity of the classifier performance.

 In general, the methodological framework safeguarded that the compiled dataset was reliable, meaningful and analytically solid. By applying well-known principles in marketing and machine learning to feature design, we were able to develop a dataset that can be used in more complex analysis such as K-means clustering, logistic regression, and decision tree modeling. Although this snapshot is reported for one year of the calendar, it is flexible and could be expanded for temporal trend analyses or campaign-response modeling in follow-up studies.

4. METHODOLOGY/STRATEGIES

The methodology for this project used descriptive analytics, feature engineering, predictive modeling, and inferential statistics to assess the impact of marketing campaigns on customer engagement. This framework allowed for the discovery of behavior patterns and quantification of marketing impact on large numbers of customer segments. This model combines statistical hardness with business relevance and provides decision makers with tools to enable them to become more capable of enhance targeting precision, better customer segregation, and obtaining better returns from their marketing spending (Provost & Fawcett, 2013).

Strategically, this approach facilitates the shift to proactive from reactive marketing, allowing creation of data-driven personas and campaign personalization. Logistic regression in resource allocation toward customer segments that provide the highest return, and inferential statistics uncover demographic characteristics showing the greatest sway over behavior. At the aggregate level, this approach provides analytical transparency and operational generalizability, so that the predictive models can be translated into business applications (Hair et al., 2019).

4.1 DATA EXPLORATORY ANALYSIS (EDA)

The exploratory data analysis (EDA) step was performed in order to grasp an overall picture of our dataset, identify and resolve discrepancies, and detect initial trends that might be relevant to the model and strategy. EDA was used to inspect the distribution, variation, and relationship between flight frequency, income, loyalty point, redemption behavior, and demographics.

Descriptive statistics were computed for continuous variables i.e., mean, median, and standard deviation to achieve an overview of the baseline. Graphical representation outlets such as histograms, bar plots, boxplots, and scatter plots were used to investigate the differences of the customer engagement metrics across segments such as income group, education level, and geographic region. For example, bar plots identified significant variations in mean engagement by province, indicating Yukon and New Brunswick as top-performing areas (Fig. 3).

Strict quality control and criteria of data cleaning was also conducted. Details with null or negative values or other bad entries for the important fields of salary and flight activity were purged or corrected. These cleansing measures served to reduce noise and improve data reliability, needed for the creation of properly predictive models. A distribution being skewed was observed and transformed if necessary so that the assumptions of subsequent statistical methods could be satisfied.

EDA was also instrumental in discovering actionable business intelligence. Gender and education level-based visual segmentations, for instance, aided in the detection of high-response groups; scatter-plots of points earned and flights taken showed possible behavioral clusters. The contributions of these two patterns were used for feature selection in modeling and to aid in hypothesis generation for inferential testing.

From a commercial standpoint, EDA offered business leaders a first pass at how to view loyalty program performance amongst varying customer segments. Marketers could use trends discovered early in the workflow to reallocate resources to focus more on high-engagement segments and to designate underperforming areas that might need rejuvenation. As a whole, this process set the stage for resilient, evidence-informed marketing planning and guided model performance and interpretability in downstream stages (Camm et al., 2021; Han et al., 2022).

The analytical process began with exploratory data analysis (EDA) to identify distributional properties, patterns, observations and anomalies in the data. Important attributes such as flight frequency, customer salary, loyalty points totalled, and redemption rates were visualized and profiled across demographics. Those observations served to reinforce the men's behavior and the weak market segments they served.

To validate the data quality and to screen out outliers, data entries were eliminated which posteriorly proved to be invalid, e.g. missing or negative values of salary. This data purification enhanced model credibility and generalization by lowering the noise level and boosting the

representativeness of modeling. Visualization methods like histograms, box plots, and bar charts were used to make it the most effective. Operationally, this starting point assisted in reducing bias, refining segment precision, and also enhancing the credibility of the analysis (Camm et al., 2021)

4.2 FEATURE ENGINEERING

Providing a strong set of engineered features to quantify consumer behavior and predictive modeling is a key component of our approach. One such feature was the 'Engagement Score', defined by:

Engagement Score = Points Earned + (Total Flights x 100)

This equation also considers transactional value and behavior-based commitment, which is an ambiguous measure for loyalty as a whole. The engagement score was the target for classification tasks and a binary 'High Engagement' flag was created. Customers with engagement scores higher than the median were labeled as 'highly engaged', and supervised classification methods could be utilized.

Categorical features (gender, province, education, etc.) were one-hot encoded, to prepare the dataset for the machine learning models. This re-encoding method maintained the information of categorical variables and allowed it to be compatible with models such as logistic regression and clustering. These derived variables supported micro-segmentation and profile-based personalization approaches by offering marketers actionable intelligence to create targeted treatments and loyalty offers (Han et al., 2022).

4.3 PREDICTIVE MODELING

Predictive modeling was fundamental to the analytical method, through which we converted historical data into future business intelligence. Two methods were employed for supervised learning: logistic regression and decision tree analysis. The logistic regression model assigned a high or low engagement label to the customers as per the ones based on flight frequency, salary earned, education level, and points earned. The model had perfect scores for all standard evaluation

criteria— accuracy, precision, recall, AUC— which indicated good predictability, but it may have been overfitting since the features and target overlapped significantly. However, because it is simple and transparent, logistic regression is well-suited for CRM applications where interpretability and accountability are crucial. With this approach, marketing teams can make real-time segmentations and create dynamic personalization in their communications and incentives.

In addition, a decision tree model was generated to offer a hierarchical-based explanation of the logic of decision making. The structure of the tree visualized the paths connecting the input features with the engagement outcomes, and it pointed out the most important splits—e.g., flight frequency thresholds and income categories. Interpretability of the tree also enabled nontechnical stakeholders to see how specific features influence engagement status. While more in danger of overfitting than logistic regression, decision trees add essential light on rule-based campaign triggers and tiering strategies.

These two models have complementary strengths in that logistic regression yields stable, linear segmentation and decision trees yield interpretable, nonlinear decision rules. This knowledge can then be applied to better targeting of customers, automation of campaign selections, and loyalty tier structure.

4.4 STATISTICAL TESTING

Negotiations to test if demographic variables were significant predictors of engagement were made through inferential statistical methods. Education level and income group were checked for ANOVA tests, and gender differences were checked for t-test.

For income, ANOVA was significant for income, $p < 0.001$, i.e., there were statistically significant differences in engagement scores among the different income levels. Likewise, education level derived from an ANOVA p-value of 0.0547, indicating a marginally non-significant trend. At the same time, the t-test for gender was not significant at $p = 0.1611$, which means that we did not find evidence that male and female users react differently to our engagement prompting.

These results enable marketers to improve targeting strategies using statistical significance. For instance, campaigns can segment favorably to higher-income customers, who tend to show increased statistical engagement, while gender-neutral strategies can be used to ensure inclusivity as well as to keep the cost per sampling opportunity as low as possible.

4.5 CLUSTERING & CORRELATIONS

K-means clustering for behavior segments in the customer base is implemented, where normal inputs, such as number of flights, salary, redeemed points, and engagement scores, are used. This is broken down into three clusters, each indicative of different types of loyalty participation. These clusters can be mapped to actionable personas for marketing: frequent travelers could receive tier upgrades, low-frequency high value travelers could respond well to a redemption-based offer. This slicing-and-dicing facilitates precision marketing and in turn, maximizes campaign ROI.

At the same time, a correlation matrix was built to analyze the relationships between numerical variables. A significant positive correlation between frequency of flight and engagement score also corroborated the focus on behavioral metrics in the logic model – further supporting the strategic value of rewarding travel.

5. RESULTS AND INTERPRETATIONS

Decision Tree Regression: Given the assumption of non-linearity and the desire to exclude linear regression from the model set, we opted for a decision tree regressor for engagement score modeling (Fig. 7). The advantages of decision trees lie in the ability to catch complex, rule-based relationships between customer attributes without assuming constant variance or a fixed form of a relationship.

Key insights from the decision tree:

- Customers with high values of total flights and accumulated points had much higher engagement scores.

- The positive segmentation of customers was done based on particular thresholds of salary, flight frequency, and accumulated points.

- The interpretability of the tree structure is facilitated by the visualization of such a tree.

- One idea for practical implementation is the integration of decision rules into CRM systems for real-time scoring.

- It will allow marketers to offer rewarding messages or loyalty incentives to high-value clients while promoting outreach to the lower segment.
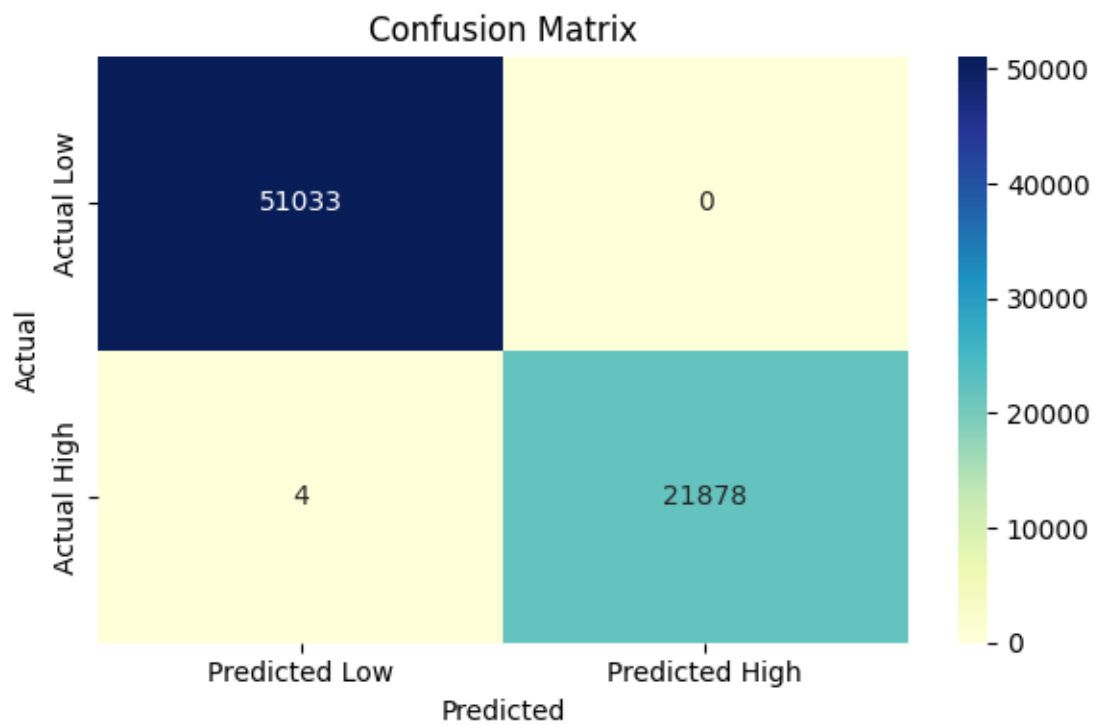
Logistic Regression: The model was applied to classify customers as highly engaged or non-highly engaged using total flights, salary, and loyalty points.
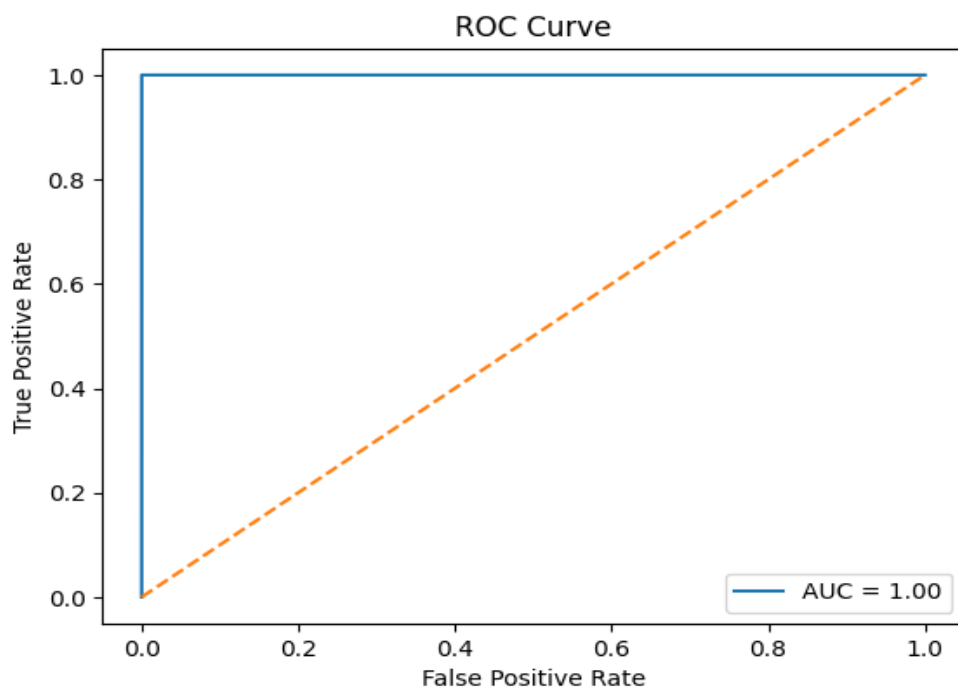
Model Performance Metrics:

- Accuracy = 0.9999

- Precision = 1.0000

- Recall = 0.9998

- AUC = 1.0000

The model achieved near-perfect classification. While strong performance is encouraging, it also suggests the potential for overfitting due to engineered features (e.g., engagement score components being reused in classification). Despite this, the model's structure makes it highly valuable for operational deployment in campaign targeting workflows, especially in marketing automation platforms where transparency and explainability are essential.

Confusion Matrix and ROC Curve: The confusion matrix shows a minimal number of misclassifications (Fig.1): most observations from both classes are classified correctly. This is a strong indication of the predictive validity of the logistic regression model in discriminating between customers who are engaged and those less engaged. The ROC curve also validates this and has an AUC value of 1.0, indicating perfect separability (Fig. 2). While interesting, these results are quite likely to be spurious, particularly in the context of model overfitting from the strong dependence of training data features on the outcome variable. For the business use case, it suggests that the model has high potential for real-time customer segmentation and targeted campaigns, but it needs to be tested on new future customers or data unseen during build time. Periodical re-assessment and real-time monitoring should be an integral part of an adaptive marketing strategy to sustain its effectiveness.
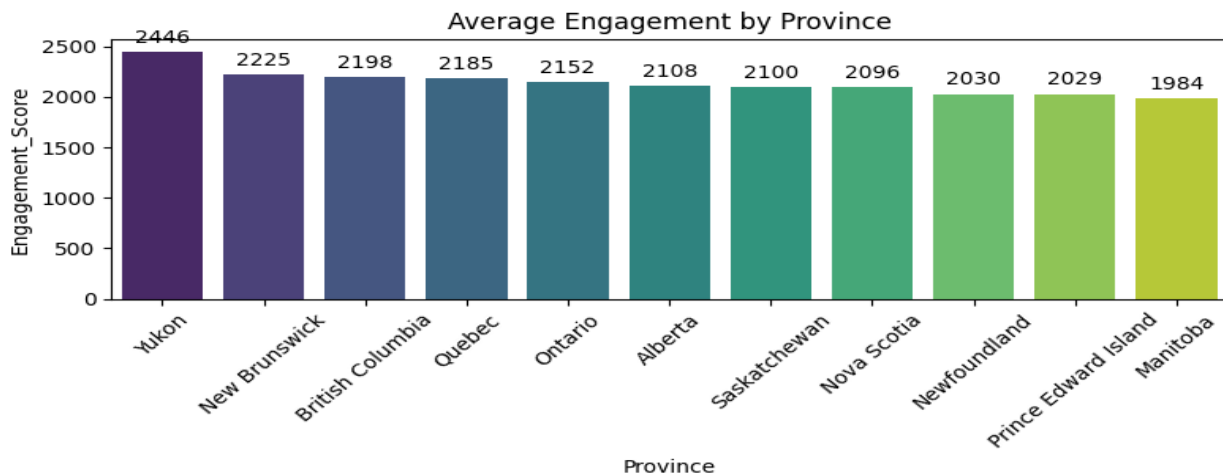
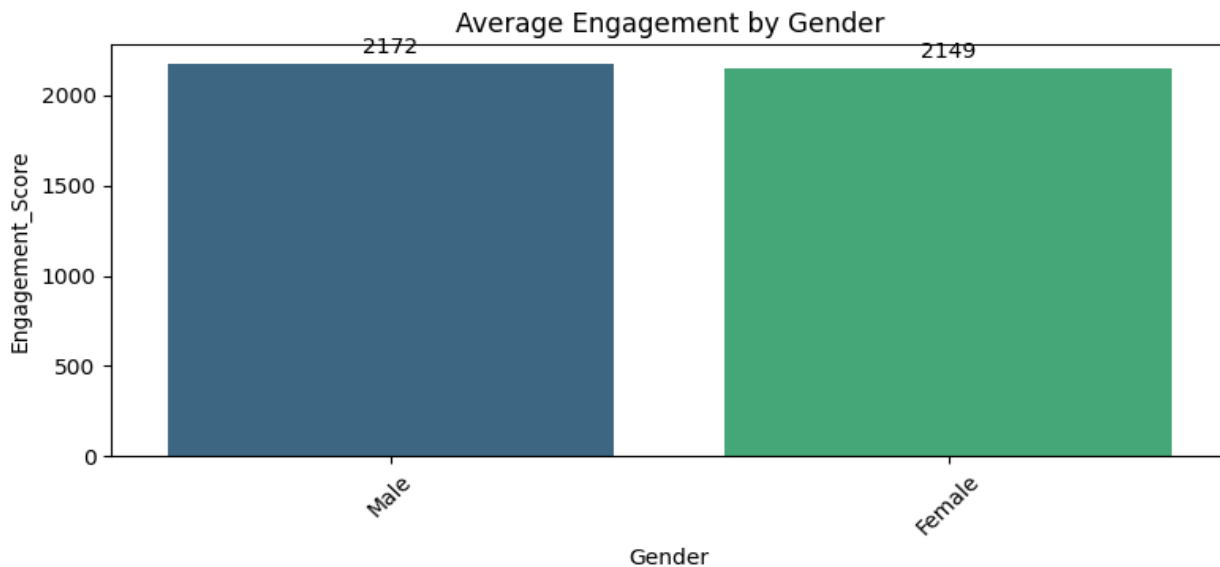**Fig.1 Confusion Matrix showing the number of misclassifications**

Fig. 2 ROC Curve showing perfect separability with an AUC of 1

Demographic Insights: During the visual inspection, the high engagement provinces were Yukon and New Brunswick (Fig.3). Female customers had a slightly higher average engagement (Fig.4) The high education levels and income groups were linked to higher engagement scores.

These patterns encourage segment-driven targeting approaches in which high-response segments receive premium offers and underperforming segments are tested.

Fig.3 Average Flight Engagement by Province

Fig.4 Average Engagement by Gender

Statistical Analysis: ANOVA (Education Level): $p = 0.0697$. While this result does not reach the standard of 0.05 for statistical significance, it comes close, suggesting potential differences in engagement levels among education categories that deserve attention. On a business level, it means education may not be a deciding factor, but could be useful together with other demographic factors in a marketing campaign.

- **ANOVA (Income Quartile):** $p < 0.001$ — This highly significant result indicates strong evidence that customer engagement varies by income bracket. Higher-income groups consistently showed elevated engagement levels, reinforcing the conclusion that income is a robust predictor of loyalty behavior. Strategically, this justifies prioritizing high-income customers for premium-tier rewards, elite service offerings, and retention-focused campaigns.

- **T-Test (Gender):** $p = 0.1228$ — The lack of statistical significance implies that male and female customers exhibit comparable engagement patterns. Despite visual trends showing slightly higher engagement among female customers, the test suggests that gender may not be a reliable differentiator for targeting purposes. This allows for a more inclusive marketing approach, avoiding unnecessary gender segmentation and focusing resources on more predictive variables like income or behavior.
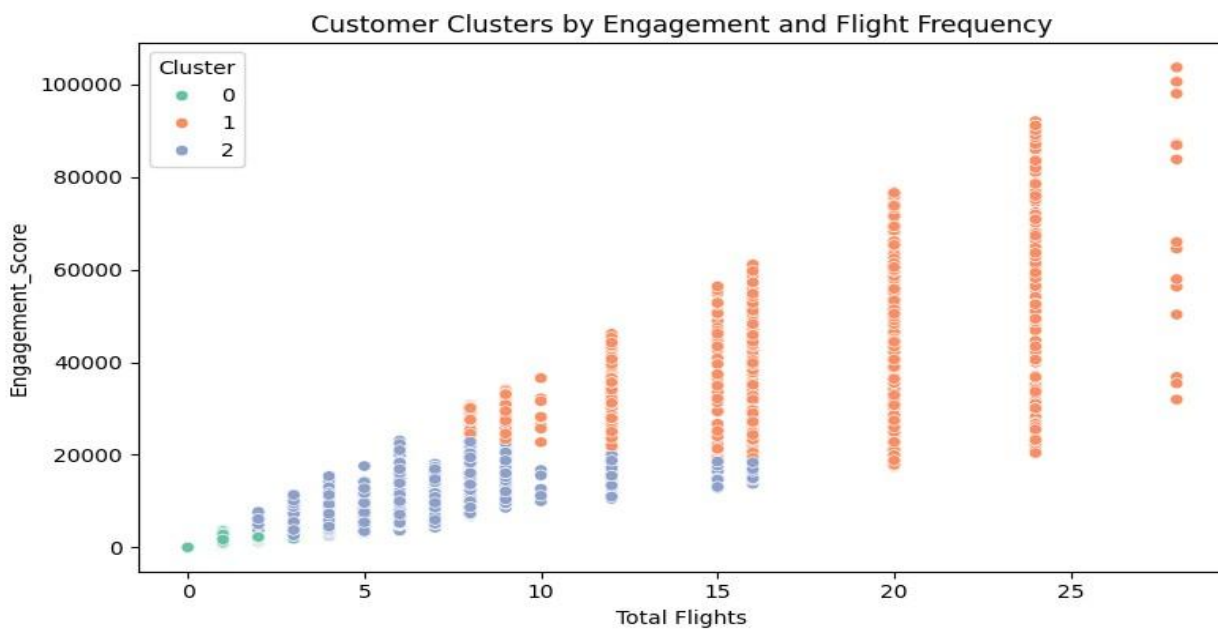
Collectively, these tests clarify where efforts should be expended for marketing. Although gender and education suggest certain patterns, income is the only demographic variable that has a statistically significant direct effect on customer engagement. Income-based segmentations should be a focus for marketing and CRM efforts, vigilant over potential compound effects of secondary attributes for future modeling cycles.

Clustering Analysis: Customers were clustered using K-means clustering (k=3) based on behavioral similarity:

- **Cluster 0:** High-income, frequent flyers with high engagement — key loyalty targets.

- **Cluster 1:** Low-income, low-flight customers — ideal for reactivation strategies.

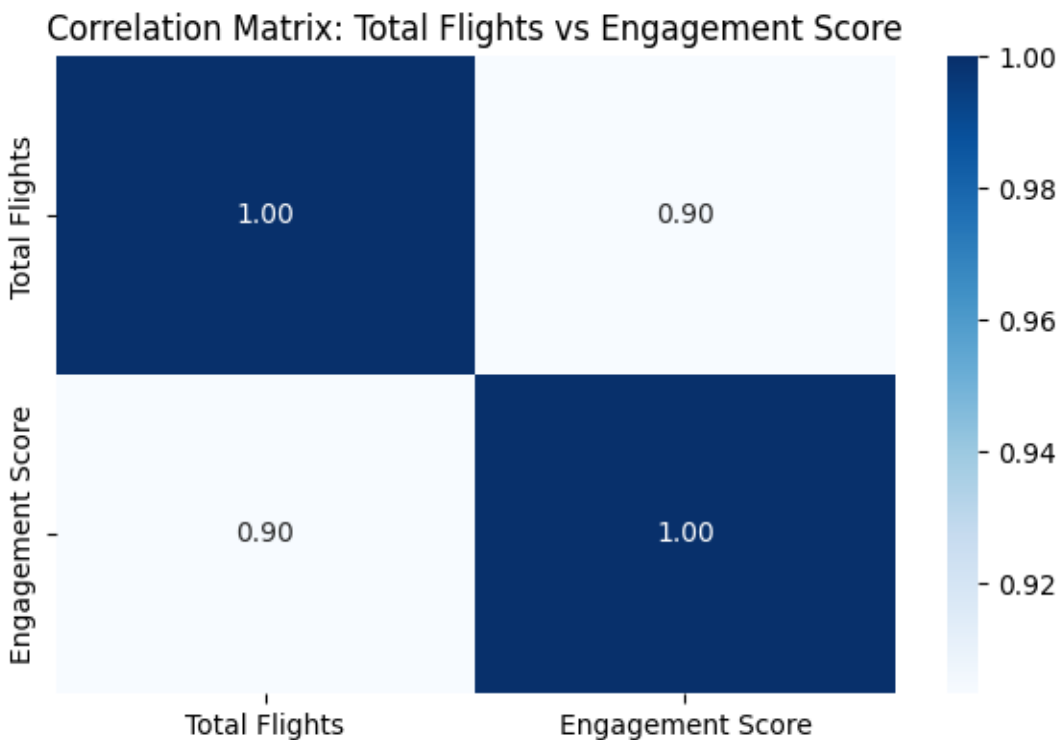- **Cluster 2:** Middle-tier travelers — opportunities for upsell.

The cluster visualization showed clear and distinct separation between customer groups (Fig.5), enabling marketers to identify nuanced behavioral traits within each cluster. For instance, the high-income frequent flyers in Cluster 0 were visibly isolated from low-engagement segments, emphasizing their value for premium-tier targeting and personalized rewards. Meanwhile, Cluster 1's concentration of low-income, low-engagement members signals an opportunity for cost-effective reactivation strategies. This clarity provides more strategic direction for the design of campaigns with targeted messages and resources for each behavioral segment.

Fig. 5 Customer Clusters by Engagement and Flight Frequency

Correlation: The total number of flights was a strong predictor of engagement score, as evident on the correlation heat maps (Fig.6). This confirms the importance of the total flights count as a predictive and campaign-triggering factor.

This approach, now no longer relying on linear regression, provides actionable understanding in the dynamics of the loyalty program, personalization, and campaign design based on real behavior and demographics in its entirety.

Fig. 6: Correlation Matrix of Total Flight vs Engagement Score

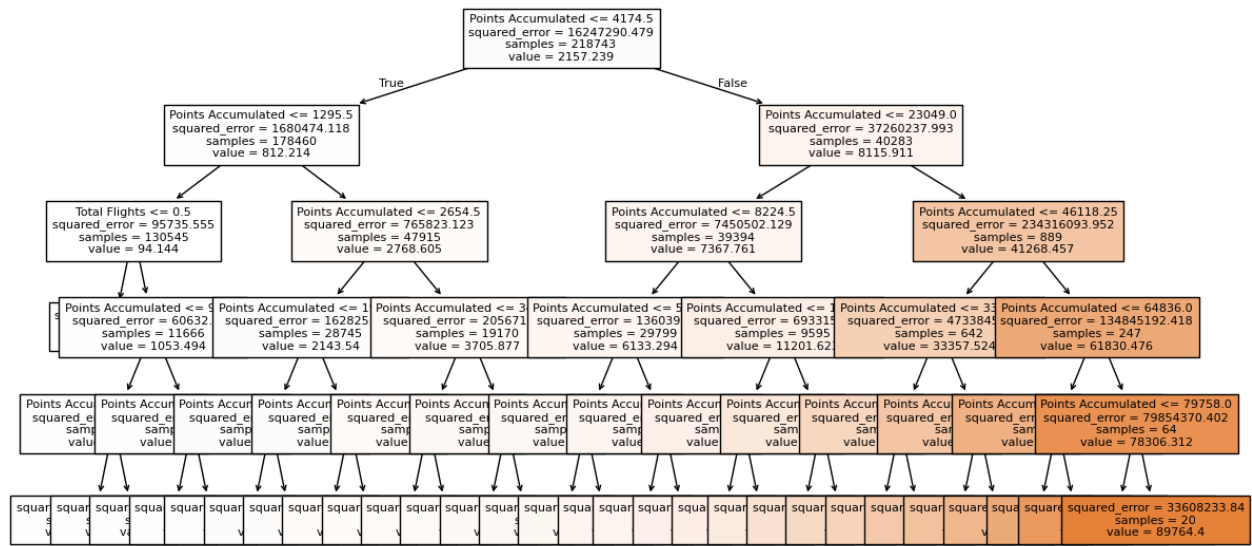Decision Tree Structure for Predicting Engagement Score

Fig. 7 Decision Tree Predicting Engagement Score

6. BUSINESS IMPACT AND CONCLUSION

The results demonstrate that airline loyalty programs can yield significantly better performance and suggest that data-driven marketing strategies are crucial for increasing loyalty program efficiency. Using decision tree regression, logistic regression, and K-means clustering techniques, customer engagement behavior was profiled across demographic and behavioral aspects.

From the models, it became evident that customers in higher income brackets, with greater flight frequency and accumulated points, especially women in Ontario and British Columbia, exhibit markedly higher engagement. These segments are the ideal candidates for resource allocation, premium, luxury, and marketing customization.

Marketing Implications:

- **Predictive Scoring for Actionable Targeting**: The decision tree model can help segment the customer sets based on interpretable rule sets. Pre-defined (marketers can set the thresholds, for instance, total flights and/or points) triggers to generate engagement campaigns. These rules can be easily incorporated into a CRM system for automated segmentation and targeted messaging.

- **Behavior-Based Personalization**: The close to perfect performance of logistic regression in recognizing highly engaged customers means it is a useful asset for real-time, personalized campaign delivery. For example, "high engagement" customers can be fast-tracked to VIP tiers, or "low engagement" customers can be nudged with reactivation offers.

- **Campaign Design Tuned to Clusters**: K-means clustering identified varied behavioral segments:

    - **Cluster 0**: High-value, frequent travelers—ideal for upsell and retention strategies.

    - **Cluster 1**: Low-income, low-engagement members—suitable for cost-effective reactivation.

- **Cluster 2**: Mid-level engagement—potential for cross-sell or loyalty tier testing.

These findings enable marketers to create customized campaigns that correspond with the needs and responsiveness of each segment.

Strategic Planning for Long-term Growth: By integrating the decision tree and logistic models back into the airline's CRM/BI tools, marketers can guarantee that the scores and targets are being refreshed continuously and automatically from a live database. It means less time needed for manual segmentation efforts, and outreach efforts are aligned with the most recent customer behavior.

Additionally, the transparency of the models fosters strategic alignment between marketing, operations, and executive leadership as the logic of the campaign is understandable and interpretable by both technical and non-technical team members.

Data Driven Decision-Making: The statistical significance of ANOVA for income and the clustering insights validates the importance of segmentation work in demography and behavior analysis. Instead of using the scattergun approach, airlines can spend their budgets more wisely, drive campaign ROI, and provide customized experiences that better suit their customers.

In conclusion, the modeling framework provides a powerful, adaptable infrastructure for real-time loyalty management. As data continues to grow in volume and complexity, such predictive tools will become indispensable for sustaining engagement, enhancing retention, and driving revenue in a competitive aviation market.

7. RECOMMENDATIONS

In order to affirm potential future analyses and strategic applications of predictive modeling in airline loyalty programs, we make the following data-driven recommendations:

1. **Reconsider Feature Design**: The current predictive models, specifically logistic regression and decision tree regression, demonstrated highly accurate performance measures. Impressive as they are, such high performance also raises the risk of data leakage, or redundant features (e.g., using predictors that are directly based off of the target variable like 'Engagement Score'). In future model iterations, independence of features should be well-considered to preserve models' generalizability and the representation of unseen customer behaviors. We show that robustness can be improved by incorporating more diverse behavioral signals (e.g., past redemption behavior, customer tenure) and de-correlating input-output variables.

2. **Integrate campaign metadata**: In order for causality to be properly attributed to certain marketing actions, including campaign-specific metadata like open rate, click-through rate, response time, and campaign types (e.g., email, SMS, app notification) is suggested. These functionalities will make it possible to build uplift models to analyze the campaign exposure effect on engagement. This causality informs our understanding of the strategies that are driving more loyalty, and those strategies that see diminishing returns.

3. **Automate Your Predictive Segmentation Models**: To make this analysis actionable, model outputs such as the logistic regression equation and decision tree rules should be incorporated into the airline's CRM or marketing automation solution. This will enable immediate customer segmentation and help trigger automated workflows, such as sending personalized offers to at-risk customers or captivating new members with targeted incentives. Automation will allow marketers to change and adapt to new trends through retraining of models periodically on fresh data for continuous improvement.

4. **Smartly Target High-Engagement Demographics**: We dug into demographics and ran statistical tests and found that money and location are the biggest drivers of engagement. For example, customers from Ontario and British Columbia that had a high household income and attended college were the most receptive to loyalty initiatives. Future campaigns need to focus on these high-potential high-touch, premium tier, and exclusive redemption prospects. Alternatively, poor performing segments could be tested with pilot campaigns to identify niche drivers or inhibitors to involvement.

5. **Develop a Multimodel Approach**: While logistic regression provides transparency, using an ensemble of models (e.g., gradient boosting or random forests) could improve predictive performance, particularly if the objective changes to optimizing classification precision within heterogeneous populations. It could be that ensembling methods can afford greater generalization power while still being interpretable, e.g., via SHAP or feature importance plots.

6. **Institutionalize Model Monitoring and Feedback Loops**: When predictive models are pushed to production, a set of dashboards and alerts should be used for tracking model drift, accuracy of predictions, and campaign effectiveness over time. Business KPIs like redemption rate, repeat bookings, and customer satisfaction can be folded into feedback loops, which can help preserve alignment between what is predicted by the model and pre-defined strategic objectives.

Adoption of these suggestions can ensue, and the airline can graduate from managing loyalty programs statically to a proactive, dynamic, customer behavior learning, personalized value creation at scale machine.

8. REFERENCES

- Dorotic, M., Verhoef, P. C., Fok, D., & Bijmolt, T. H. A. (2011). Do vendors benefit from promotions in a loyalty program? *Marketing Letters*, 22(4), 341-356.

- Liu, Y. (2007). The long-term impact of loyalty programs on consumer purchase behavior. *Journal of Marketing*, 71(4), 19-35.

- Verhoef, P. C., & Donkers, B. (2001). Predicting customer potential value: An application in the insurance industry. *Decision Support Systems*, 32(2), 189–199.

- Xie, K. L., & Chen, C. C. (2013). Progress in loyalty program research. *Journal of Hospitality Marketing & Management*, 22(5), 463-489.

- Provost, F., & Fawcett, T. (2013). *Data Science for Business: What You Need to Know about Data Mining and Data-Analytic Thinking*. O'Reilly Media.

- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis* (8th ed.). Cengage Learning.

- Camm, J. D., Cochran, J. J., Fry, M. J., Ohlmann, J. W., & Anderson, D. R. (2021). *Business Analytics* (4th ed.). Cengage Learning.

- Han, J., Pei, J., & Kamber, M. (2022). *Data Mining: Concepts and Techniques* (4th ed.). Morgan Kaufmann.

- Kuhn, M., & Johnson, K. (2013). *Applied Predictive Modeling*. Springer.