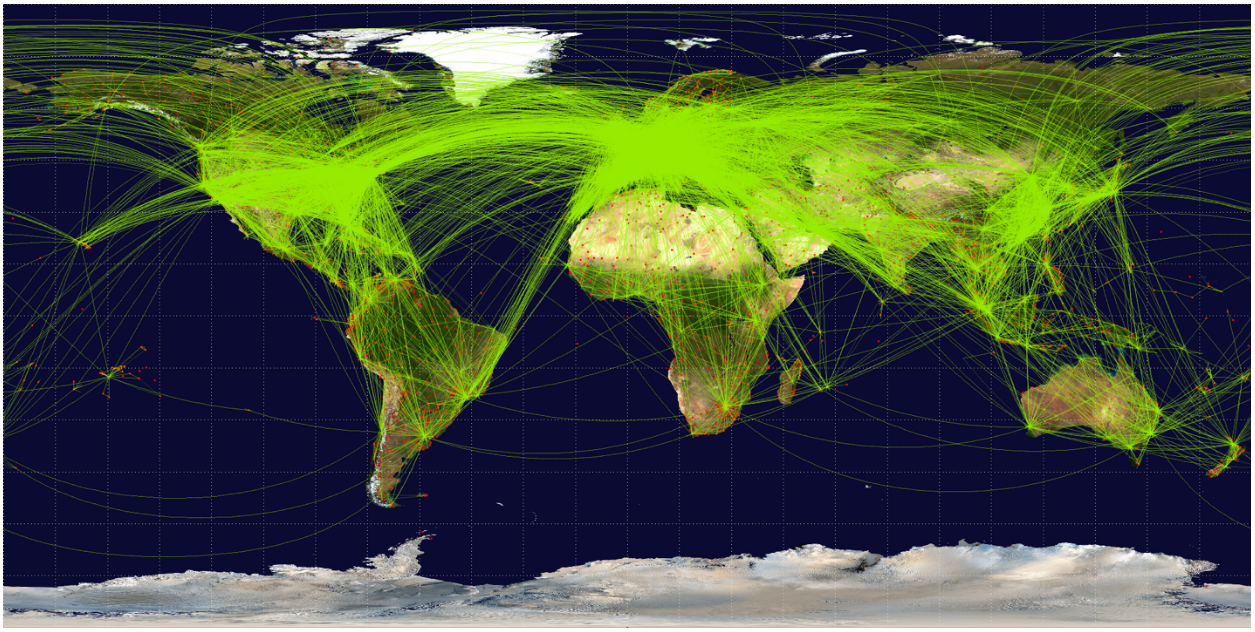


Image: wikimedia.org

Invistico Airlines Project Report: 1st case

For 1st and 2nd case code: https://github.com/izsolnay/Invistico_Airlines_Python

Objectives

1st case

Invistico Airlines is interested in learning if a better inflight entertainment experience leads to higher customer satisfaction. They would like the construction and evaluation of a model that predicts whether a future customer would be satisfied with their services given previous customer feedback about their inflight entertainment experience.

Data

The data is sample size of survey responses from 129,880 customers. It includes data points such as satisfaction, class, flight distance, and inflight entertainment, among others. It is an in-house product.

Deliverables

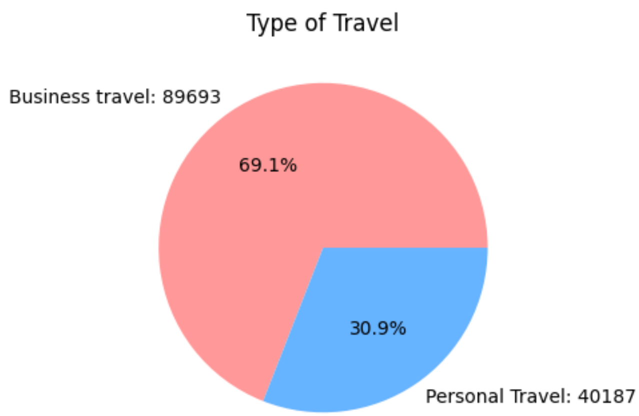
Models: binomial logistic regression, decision tree, random forest, XGBoost.
(Since this project is a portfolio addition, the models are predetermined. Since this is a labelled data set, all models qualify as supervised.) Python Jupyter notebooks were used for all coding.

1st case: Binomial logistic regression model (1st notebook)
In the first case, the airline is interested in learning whether a better inflight entertainment experience leads to higher customer satisfaction. The outcome (dependent y variable) is satisfaction a categorical Boolean variable (yes or no). The selected predicting (independent X variable) is inflight entertainment. (In point of

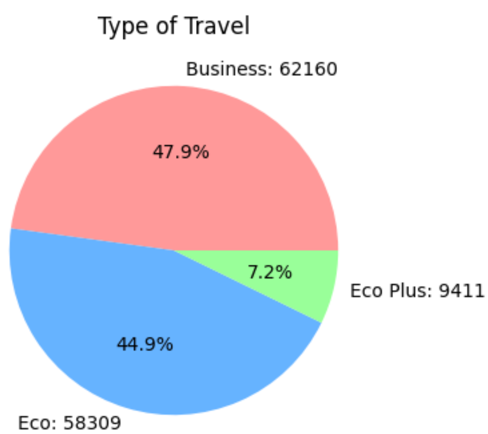
fact, many of the variables in the data set could be employed for the model. However, the results from the following tree-based models suggest that inflight entertainment is the most predictive variable.) For this task, a binomial logistic model (rather than linear) is appropriate. Binomial logistic regression is a statistical technique that models the probability of an event (satisfaction) based on one (or more) independent variables (inflight entertainment). The outcome must be a binary classification (satisfaction/dissatisfaction). Customers were asked to rate their experience of inflight entertainment using a 1-5 score.

Reasons for travel and cabin classes flown

Approximately 69% of the 129,880 customers surveyed travelled for business purposes and 30% travelled for personal reasons:

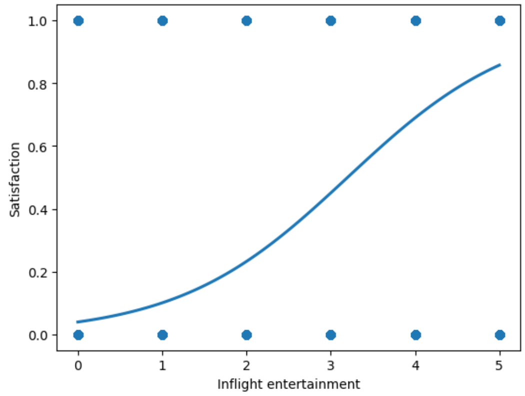


Of these, roughly 48% travelled in business class, roughly 45% in Economy, and about 7% in Economy Plus:



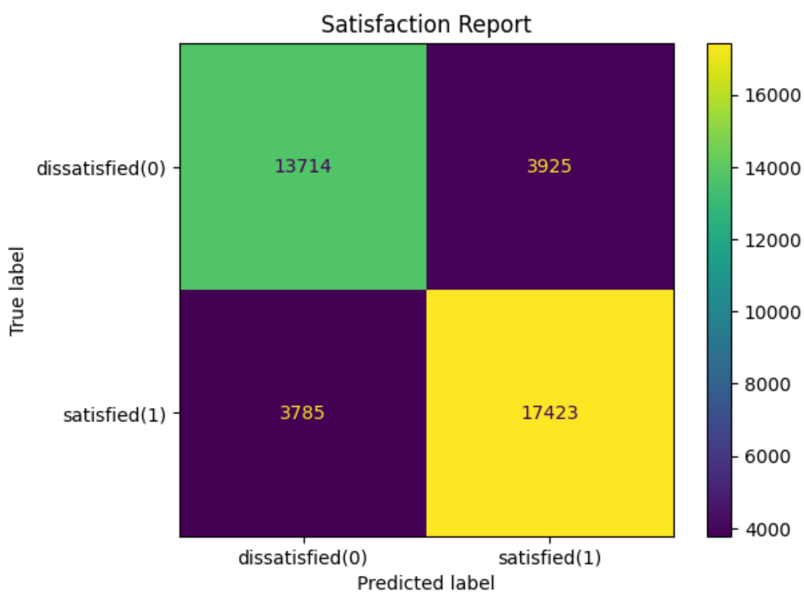
Results of Logistic regression

This model used the variable Inflight entertainment as the independent predictive variable to predicate whether the inflight entertainment experiences of previous customers would suggest future customer satisfaction. Previous customers rated their inflight entertainment experiences using a 1-5 rating scale. These customers had at the same time the opportunity to judge their overall satisfaction of their airline experience by selecting yes or no. This binary variable satisfaction served as the dependent y variable for the logistic regressive model. The model predicts a strong and steady correlation between those who rated inflight entertainment highly and their general satisfaction with airline experience. The more customers said they enjoyed the inflight entertainment, the more likely they were to be satisfied.

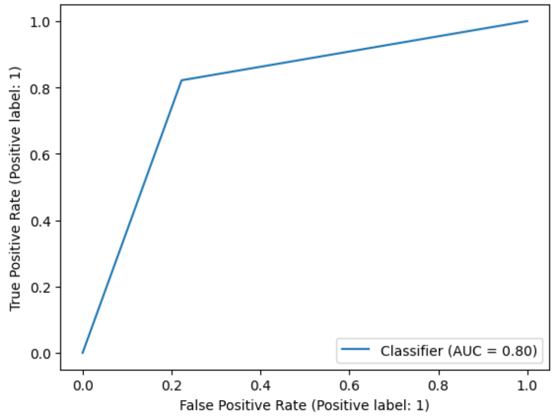


Test data

From the 38,847people in the test data, 21,208 were satisfied. Of those, the model captures 17423 satisfied customers – missing fewer than 4,000 satisfied customers.

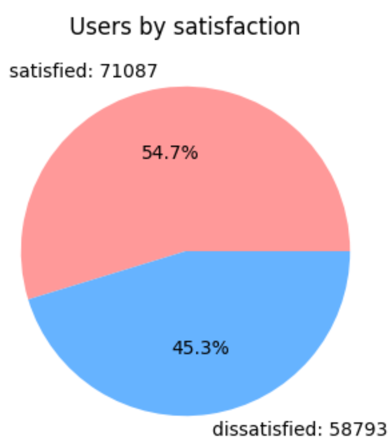


Since the goal of this project is to identify whether the inflight entertainment experiences of previous customers would suggest future customer satisfaction, this model is very good at correctly identifying satisfied customers and predicting their satisfaction based solely on their previous inflight entertainment experience. It scored ~82% on both recall and precision scores (with a f1 of ~82%), thus it has an equally high ability to identify satisfied or unsatisfied customers and an equally low chance of falsely identifying satisfied or unsatisfied customers (Type I and Type II errors). Further demonstrating this model's efficacy, it achieved an AUC score of ~80%, which suggests that it has better overall performance (over all possible classification thresholds) in distinguishing between positive and negative classes.



In an effort to identify even more satisfied customers based on their previous inflight entertainment experience, the model could be optimized based on recall score. However, if it is so tuned, it will become more sensitive to finding satisfied people and could be prone to incorrectly categorizing people as satisfied (false-positives/Type-I error) when they are dissatisfied, thereby giving a false impression of satisfaction. If, on the other hand, the airline would prefer to play it safe, the model could be optimized based on precision score. This would lead to the model attempting to reduce the occurrences of incorrectly classifying people as satisfied when they are dissatisfied (false positives/Type I errors). However, in its goal to be precise (not classify people as satisfied when they are dissatisfied), the algorithm can become more selective. A higher rate of precision may mean that more samples are classified as dissatisfied, when then are satisfied (false-negative/Type II errors). Thus, satisfied customers could be missed which could lead to the airline making changes where none are needed.

The model also had an ~82% accuracy score, this is far better predictor of satisfaction than the ~55% satisfaction rating for the overall dataset:



The success of the model indicates that the airline should focus attention on their inflight entertainment service, either leaving it as it is or continuing to improve it based on customer feedback.