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AIRLINE CUSTOMER SATISFACTION

GROUP 25

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TABLE OF CONTENTS

INTRODUCTION

1.1 Background

Customer satisfaction is a fundamental performance metric for airlines. Regular reviews of an airline's performance under this metric is a necessary technique to measure overall performance, as well as the factors contributing to its ability to meet revenue goals and the business aims set by key stakeholders. An important task when measuring customer satisfaction is conducting regular customer surveys. These surveys must be of ample size, large enough to be statistically significant and an adequate sample representative of the customer base. Using these surveys, key factor decomposition steps in business analytics can be taken to measure the areas and services where the airline is performing well, as well as areas where the airline needs to improve. Further, it allows airlines to make efficient use of capital by allocating maximally efficient budgets to the most significant contributing services that are the most underperforming.

In 2022, customer satisfaction dropped by 8% due to the rampant cancellations of that year. Despite this, the industry as a whole increased by 1% over the previous year. The necessity of business analytics is in that it can clarify an otherwise counterintuitive result, allowing airlines not to overlook underperforming services despite improvements on the annual term.

1.2 Methodology

The standard methodology of CRISP-DM will be followed, as illustrated below. This begins with gaining a business understanding, establishing the business aims, research objectives, project outcomes and key performance indicators. With reference to this business understanding, the scope of the project is defined.

Subsequently, an understanding of the data, it's structure, characteristics and limitations will follow. At each stage, it maybe necessary to iteratively revisit prior phases of the cycle to ensure new discoveries are reflected and propagated through our pipeline. This includes data preparation, including cleaning, preprocessing and, as and when appropriate, feature engineering and dimensionality reduction to prepare one or more subsets for comparative modelling. Modelling then follows based on the preparation phase, evaluating based on predefined metrics and iteratively revisiting the previous phases as explained. Deployment is out of the scope of this project, but in such a case, continuous monitoring and regular re-training is required to deal with phenomenons such as data drift or concept drift.

Introduction

2.1 The Dataset

The dataset was sourced from Kaggle at https://www.kaggle.com/datasets/teejmahal20/airline-passenger-satisfaction. It consists of survey responses by customers of an airline, rating various aspects of their flight experience on scale of 1 to 5. There are 25 features across a training set and test set with cumulative size of 129,880 records. The visualisation of this data in tabular form is below.

2.1.1 Suitability

The dataset was selected as it satisfied the conditions stated under section **1.1**. These were that the dataset must be set of customer survey response data that is of significant enough size that it can be deemed representative of the entire customer base. It is also suitable due to being a mix of both quantitative and qualitative survey responses, ensuring that there is variety in the type of data processed to provided a more holistic and robust insight to the customer experience and the patterns and relationships that can be drawn from it.

2.1.2 Complexity

The large number of features allows for ample selection of feature subsets for variable preprocessing techniques and comparisons. However, it is not so high dimensional so as to detrimentally effect the performance of the models, given that there are 129,880 samples for 23 (25 less the redundant ID fields) features, with a total ratio of over 5,500 samples per feature. Further, given the relatively balanced class of the target variable, the data is suitable because any further class balancing would be optional rather than necessary.

2.1.3 Data Scale

Lastly, the scale of features highly contrasts between the type of the feature. For all discrete ordinal features, the data is within the same order of magnitude. However, the continuous features are in a range that is orders of magnitude larger than the discrete ordinals, but all within the same relative range (save for one feature, “Age”). The number of categorical features is within a reasonable range so as not to require extensive preparation, while also providing enough key customer and flight data.

2.2 Data Overview

In this dataset, there are:

- 14 ordinal discrete features for ratings of in and out-of flight services, such as baggage handling, inflight service, booking service;
- 4 continuous numerical features for customer age, flight distance, flight departure delay and flight arrival delay;
- 3 binary categorical features representing gender, type of flight (business or leisure), and customer type (loyal or disloyal);
- 1 categorical feature representing the flight class (economy, economy plus, business);

Introduction

2 redundant ID fields are also included. Finally, the **target** variable is a binary categorical representing customer **satisfaction**, taking values of “satisfied” or “neutral or dissatisfied”. The target variable is reasonably balanced, with 43% of customers falling under “satisfied”, and 57% “neutral or dissatisfied”. The figure below depicts a tabular view of the data and basic descriptive statistics.

— Variable type: character

	skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
1	Gender	0	1	4	6	0	2	0
2	Customer.Type	0	1	14	17	0	2	0
3	Type.of.Travel	0	1	15	15	0	2	0
4	Class	0	1	3	8	0	3	0
5	satisfaction	0	1	9	23	0	2	0

— Variable type: numeric

	skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
1	X	0	1	44159.	31207.	0	16235.	38964.	71433.	103903	
2	id	0	1	64940.	37493.	1	32471.	64940.	97410.	129880	
3	Age	0	1	39.4	15.1	7	27	40	51	85	
4	Flight.Distance	0	1	1190.	997.	31	414	844	1744	4983	
5	Inflight.wifi.service	0	1	2.73	1.33	0	2	3	4	5	
6	Departure.Arrival.time.convenient	0	1	3.06	1.53	0	2	3	4	5	
7	Ease.of.Online.booking	0	1	2.76	1.40	0	2	3	4	5	
8	Gate.location	0	1	2.98	1.28	0	2	3	4	5	
9	Food.and.drink	0	1	3.20	1.33	0	2	3	4	5	
10	Online.boarding	0	1	3.25	1.35	0	2	3	4	5	
11	Seat.comfort	0	1	3.44	1.32	0	2	4	5	5	
12	Inflight.entertainment	0	1	3.36	1.33	0	2	4	4	5	
13	On.board.service	0	1	3.38	1.29	0	2	4	4	5	
14	Leg.room.service	0	1	3.35	1.32	0	2	4	4	5	
15	Baggage.handling	0	1	3.63	1.18	1	3	4	5	5	
16	Checkin.service	0	1	3.31	1.27	0	3	3	4	5	
17	Inflight.service	0	1	3.64	1.18	0	3	4	5	5	
18	Cleanliness	0	1	3.29	1.31	0	2	3	4	5	
19	Departure.Delay.in.Minutes	0	1	14.7	38.1	0	0	0	12	1592	
20	Arrival.Delay.in.Minutes	393	0.997	15.1	38.5	0	0	0	13	1584	

Dataset after loading - split by datatype (“Character”, “Numeric”) with summary statistics.

Since the target is binary, this is a binary classification problem. Therefore, the following performance metrics will be used:

- **Feature Importance**: necessary to identify most influential factors of satisfaction;
- **Accuracy**: necessary to measure percentage of correctly identified/classified customers;
- **F1-Score**: important in cases of class imbalance & to give equal weighting to precision & recall;
- **ROC-AUC**: maximizing model's ability to differentiate between classes.

2.3 Model Selection

Given the large sample-to-feature ratio and the nature of the problem being a binary classification one, the following models were selected for comparison:

- **Deep Neural Network**: for its superior ability to find non-linear relationships;
- **Support Vector Machine**: for its singular decision boundary and flexibility of the kernels;
- **Decision Tree**: for simplicity and explainability;
- **Random Forest**: for enhanced capabilities on the Decision Tree
- **Logistic Regression**: for simplicity and as a standard baseline
- **K-Nearest Neighbours**: for its flexibility and consideration of locality

EDA & Preparation

3.1 Data preparation

3.1.1 Duplicate Records

Analysis of the unique record of “ID” and “X” columns showed an approximately 26,000 record discrepancy, indicating duplicate records possibly due to the combination of the train and test sets obtained, of which the test set may have been a subset of the train set already. Otherwise, it could have been due to separate indexing of the two sets of data:

```
X:        103904 id:        129880
```

Number of unique records for each column “X” and “ID”.

After filtering all duplicate records out using R, the dataset remained the same, indicating that the phenomenon was due to separate indexing. Therefore we remain with 129,880 records, still.

3.1.2 Feature types

Of the 14 discrete ordinal features, 13 features were ratings from 0 to 5 and 1 - “Baggage Handling” - was a rating from 1-5. When scaling, this (minor) difference will be addressed. Given the natural order of ratings features, these can be converted to the R “factor” data type - and then numerical at the scaling or normalisation step - and do not need to be one-hot encoded due to preservation of their natural order.

The continuous features only need to be scaled. Of all categorical features, the binary ones were dichotomous and therefore do not have a natural order, where as the “Class” feature does have a natural order. Thus, neither type of categorical needs one-hot encoding, as binary features can just represent either value using a 0 or 1, and the “Class” feature must retain its natural order. All categorical variables will be converted to R “factor” datatypes and, later, numerical types. The following depicts the transform of the feature types:

```
$ Gender                         : chr  "Male" "Male" "Female" "Female" ...
$ CustomerType                   : chr  "Loyal Customer" "disloyal Customer" "Loyal Customer"
$ Age                            : int  13 25 26 25 61 26 47 52 41 20 ...
$ TypeofTravel                   : chr  "Personal Travel" "Business travel" "Business travel"
$ Class                          : chr  "Eco Plus" "Business" "Business" "Business" ...
$ FlightDistance                 : int  460 235 1142 562 214 1180 1276 2035 853 1061 ...
$ Inflightwifiservice            : int  3 3 2 2 3 3 2 4 1 3 ...
$ DepartureArrivaltimeconvenient: int  4 2 2 5 3 4 4 3 2 3 ...
$ EaseofOnlinebooking            : int  3 3 2 5 3 2 2 4 2 3 ...
$ Gatelocation                   : int  1 3 2 5 3 1 3 4 2 4 ...
$ Foodanddrink                   : int  5 1 5 2 4 1 2 5 4 2 ...
$ Onlineboarding                 : int  3 3 5 2 5 2 2 5 3 3 ...
$ Seatcomfort                    : int  5 1 5 2 5 1 2 5 3 3 ...
$ Inflightentertainment          : int  5 1 5 2 3 1 2 5 1 2 ...
$ Onboardservice                 : int  4 1 4 2 3 3 3 5 1 2 ...
$ Legroomservice                 : int  3 5 3 5 4 4 3 5 2 3 ...
$ Baggagehandling                : int  4 3 4 3 4 4 4 5 1 4 ...
$ Checkinservice                 : int  4 1 4 1 3 4 3 4 4 4 ...
$ Inflightservice                : int  5 4 4 4 3 4 5 5 1 3 ...
$ Cleanliness                    : int  5 1 5 2 3 1 2 4 2 2 ...
$ DepartureDelayinMinutes        : int  25 1 0 11 0 0 9 4 0 0 ...
$ ArrivalDelayinMinutes          : num  18 6 0 9 0 0 23 0 0 0 ...
$ satisfaction                   : chr  "neutral or dissatisfied" "neutral or dissatisfied"
```

```
$ Gender                         : num  1 1 0 0 1 0 1 0 0 1 ...
$ CustomerType                   : num  0 1 0 0 0 0 0 0 0 1 ...
$ Age                            : int  13 25 26 25 61 26 47 52 41 20 ...
$ TypeofTravel                   : num  1 0 0 0 0 1 1 0 0 0 ...
$ Class                          : num  3 1 1 1 1 2 2 1 1 2 ...
$ FlightDistance                 : int  460 235 1142 562 214 1180 1276 2035 853 10
$ Inflightwifiservice            : int  3 3 2 2 3 3 2 4 1 3 ...
$ DepartureArrivaltimeconvenient: int  4 2 2 5 3 4 4 3 2 3 ...
$ EaseofOnlinebooking            : int  3 3 2 5 3 2 2 4 2 3 ...
$ Gatelocation                   : int  1 3 2 5 3 1 3 4 2 4 ...
$ Foodanddrink                   : int  5 1 5 2 4 1 2 5 4 2 ...
$ Onlineboarding                 : int  3 3 5 2 5 2 2 5 3 3 ...
$ Seatcomfort                    : int  5 1 5 2 5 1 2 5 3 3 ...
$ Inflightentertainment          : int  5 1 5 2 3 1 2 5 1 2 ...
$ Onboardservice                 : int  4 1 4 2 3 3 3 5 1 2 ...
$ Legroomservice                 : int  3 5 3 5 4 4 3 5 2 3 ...
$ Baggagehandling                : int  4 3 4 3 4 4 4 5 1 4 ...
$ Checkinservice                 : int  4 1 4 1 3 4 3 4 4 4 ...
$ Inflightservice                : int  5 4 4 4 3 4 5 5 1 3 ...
$ Cleanliness                    : int  5 1 5 2 3 1 2 4 2 2 ...
$ DepartureDelayinMinutes        : int  25 1 0 11 0 0 9 4 0 0 ...
$ ArrivalDelayinMinutes          : num  18 6 0 9 0 0 23 0 0 0 ...
$ satisfaction                   : num  0 0 1 0 1 0 0 1 0 0 ...
```

Data pre-transform (left) and post-transform (right) of categorical to factor and then numerical.

3.1.3 Missing Values

Of the 129,880 samples, only 393 had missing values, equating to approximately 0.3% of the dataset which is quite insignificant. All 393 missing values belonged to the “ArrivalDelayInMinutes” feature. Rudimentary data imputation techniques would involve mean, median or mode imputation - a more robust approach would include prediction of these values by some means, for example, linear regression. Given the relatively insignificant proportion of missing values, a comparison of these approaches would likely cause inconsequential changes in the feature-wise distribution of the data, which means a comparison of these changes will likely yield almost identical results. So, we opted to proceed with more robust approach for imputation, using linear regression, detailed later.

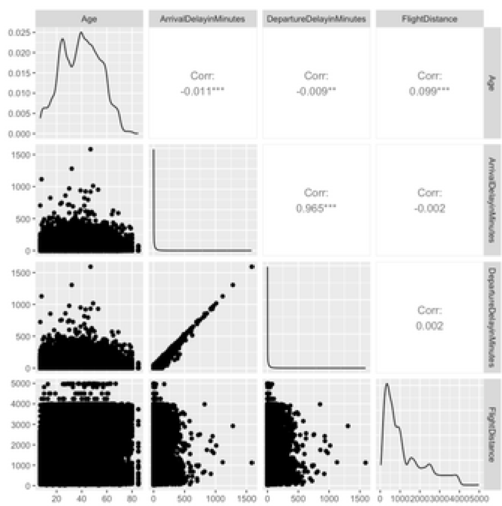
3.2 Descriptive Statistics

3.2.1 Distribution

Continuous Features

Notably, the distribution of both “ArrivalDelayInMinutes” and “DepartureDelayInMinutes” features has significant (mutually comparable) positive skew. Their relative similarity also confirms the intuition that the features are likely extremely collinear, given that both features relate to the delay of the same flight at different points, where planes are unlikely to alter their flight speed, path or other characteristics due to a number of constraints, including fuel consumption, pre-programmed schedules, air traffic and regulations, among others.

Another feature with a skewed distribution is “FlightDistance”, which can be reasoned for due to the general relationship that further flights are more expensive, which less people are able to pay for. As expected, the “Age” feature exhibited an approximately standard Gaussian/Normal distribution. Plots for the distribution and summary statistics are shown below.



Field	Catagorical	Symbols	Name	Min	Mean	Max	Skew
Age	✖ No	-	0	7.00	39.43	85.00	-0.00
ArrivalDelayinMinutes	✖ No	-	0	0.00	15.09	1,584.00	6.67
DepartureDelayinMinutes	✖ No	-	0	0.00	14.64	1,592.00	6.85
FlightDistance	✖ No	-	0	31.00	1,190.21	4,983.00	1.11

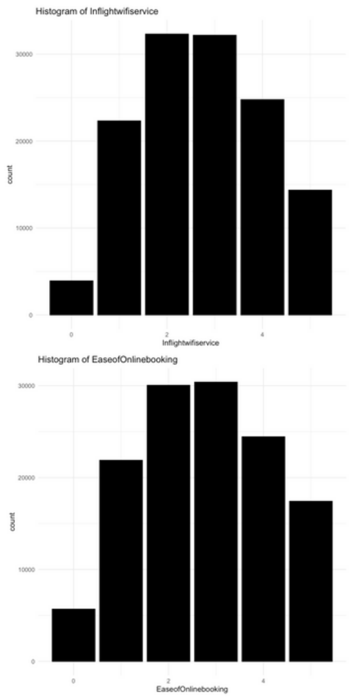
Pair & Pearson correlation plot (left) and descriptive statistics (right) including skew of continuous features.

Discrete/Categorical Features

Of all the ratings, none exhibit any significant skew. Further, the categorical features are fairly imbalanced, except for the target features. Example plots of their respective chart and descriptive statistics follow. Note: a more representative statistic description of the discrete features (ratings) might be the relative quantiles, detailed in the initial table describing the data in section **2.2**.

Field	Catagorical	Symbols	Name	Min	Mean	Max	Skew
Gender	✔ Yes	2	Female(51%)	-	-	-	-
CustomerType	✔ Yes	2	Loyal Customer(82%)	-	-	-	-
TypeofTravel	✔ Yes	2	Business travel(69%)	-	-	-	-
Class	✔ Yes	3	Business(48%)	-	-	-	-
satisfaction	✔ Yes	2	neutral or dissatisfied(57%)	-	-	-	-

Pair & bar plot (left) and descriptive statistics (right) including skew of continuous features.



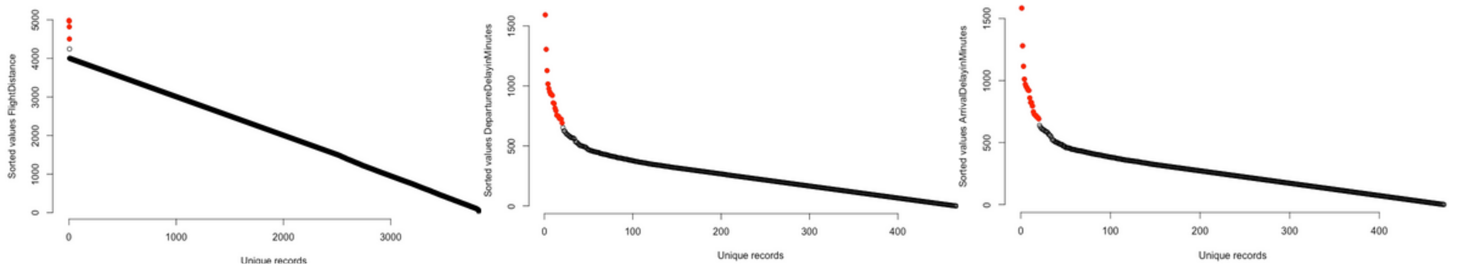
Field	Catagorical	Symbols	Name	Min	Mean	Max	Skew
Inflightwifiservice	✖ No	-	0	0.00	2.73	5.00	0.04
DepartureArrivaltimeconvenient	✖ No	-	0	0.00	3.06	5.00	-0.33
EaseofOnlinebooking	✖ No	-	0	0.00	2.76	5.00	-0.02
Gatelocation	✖ No	-	0	0.00	2.98	5.00	-0.06
Foodanddrink	✖ No	-	0	0.00	3.20	5.00	-0.16
Onlineboarding	✖ No	-	0	0.00	3.25	5.00	-0.46
Seatcomfort	✖ No	-	0	0.00	3.44	5.00	-0.49
Inflightentertainment	✖ No	-	0	0.00	3.36	5.00	-0.37
Onboardservice	✖ No	-	0	0.00	3.38	5.00	-0.42
Legroomservice	✖ No	-	0	0.00	3.35	5.00	-0.35
Baggagehandling	✖ No	-	0	1.00	3.63	5.00	-0.68
Checkinservice	✖ No	-	0	0.00	3.31	5.00	-0.37
Inflightservice	✖ No	-	0	0.00	3.64	5.00	-0.69

Example bar plots (left) and descriptive statistics (right) including skew of discrete features.

Intuitively, the more negative the skew of the ratings features, the higher the satisfaction of the customers with those services.

3.3 Outlier Detection

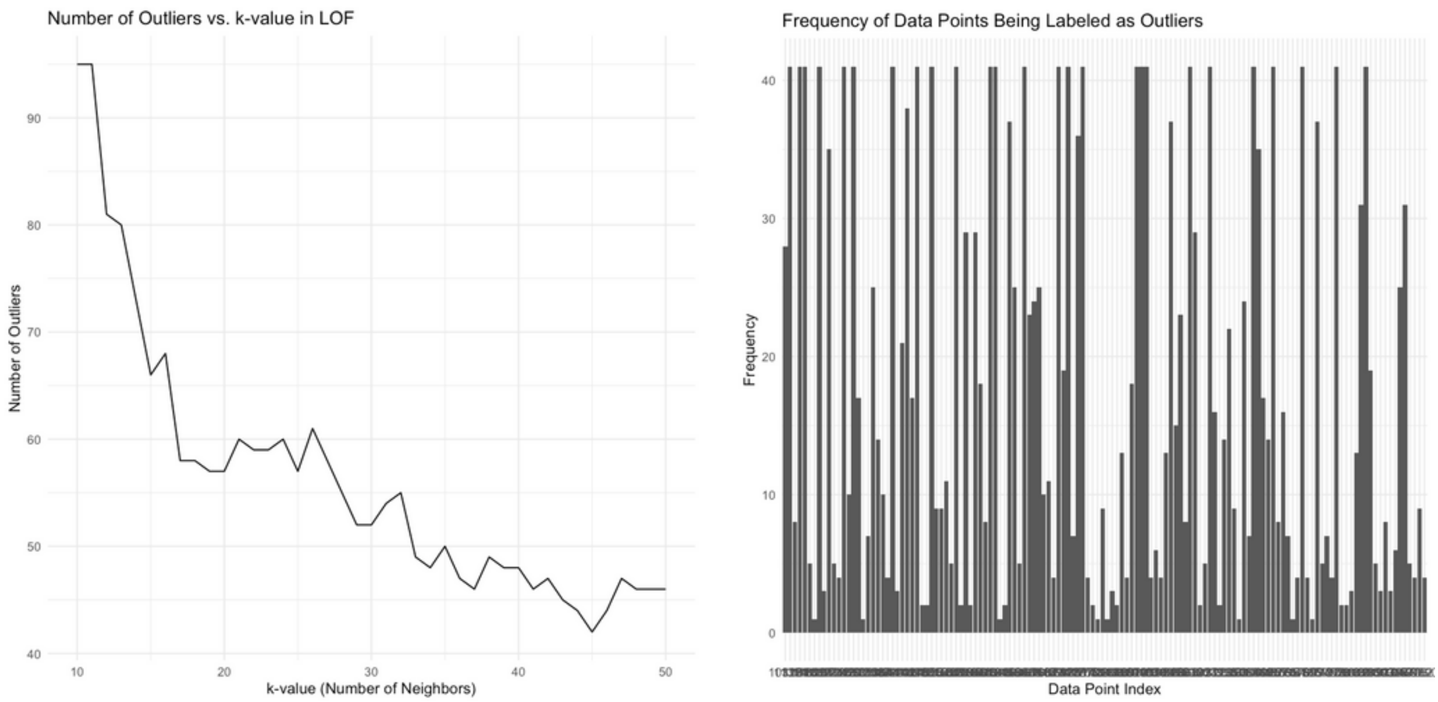
Rudimental outlier analysis detected 4 outliers in “FlightDistance”, and 20 in each of the delay-related features using the chi-squared test with a confidence interval of 0.95. Given that the distribution of “FlightDistance” being less skewed, this initially seems plausible. Note: this was performed after imputation of missing values via linear-regression and min-max scaling. The plots for the outliers detected in each feature are shown below.



Plots of outliers detected in "FlightDistance" (left), Departure delay (middle), Arrival Delay (right).

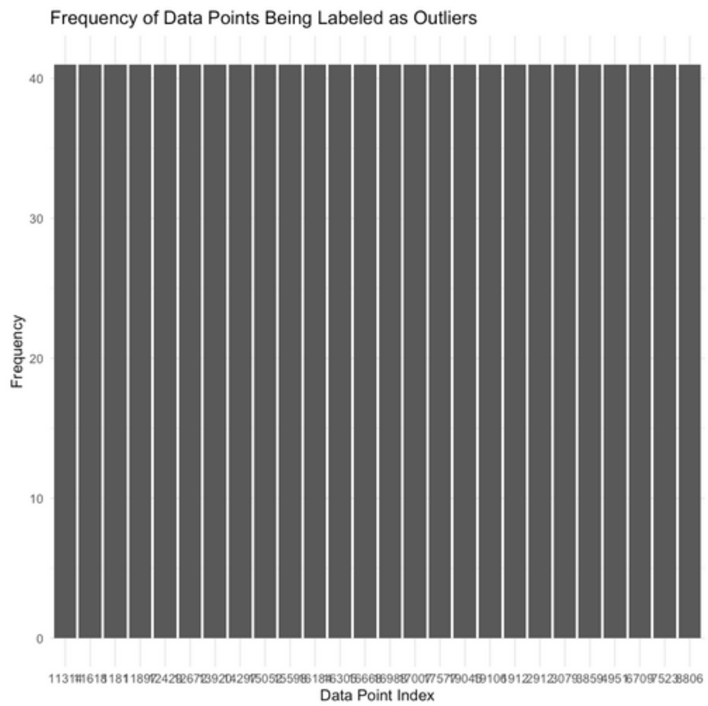
However, clearly, more robust outlier detection methods are required. Given the dataset's skew in the aforementioned features, as well as uncertainty regarding its geometric structure (spherical or non-spherical), a density-based anomaly detection technique seemed most appropriate. Specifically, Local Outlier Factors (LOF) seemed most appropriate, since they operate similarly to DBSCAN in that outliers are determined based on local neighbourhood density (which disregards the geometric shape of the data, unlike distance based techniques such as *k*-means), but it also considers a "local reachability" of one point from its neighbours, which means that the distance metrics used are asymmetrical, giving us more precise anomaly detection.

Since LOF is extremely sensitive to the hyper-parameters *K* (neighbourhood size), a reasonable heuristic range of values for *K* ~ [10, 50] inclusive was selected and iterated over for further analysis. Below is the resulting plot for the analysis on a subset of 20,000 uniformly sampled rows.



Plot showing outliers found for each *K* (left) and number of *K*-values for which each outlier was identified (right).

In the *K*-value plot (left), an "elbow" occurs at $K = 22$, where the number of outliers found is 57. When looking at the plot on the right, around 120 outliers are repeatedly identified for varying *K* values, with the a number of the most identified outliers being identified for all values of *K*. Using a confidence interval of 0.95, 26 outliers are identified, all occurring in 100% of cases. This yields a ~10 times higher proportion of outliers (0.13% as opposed to 0.015%) which, considering the skew of the data previously discussed, appears more consistent. The outliers identified using this method are presented in the bar and histogram plots on the following page. The minimum rate of occurrence is 100% using the previously stated confidence. Empirically, this tells us that, at the very least, our precision rate is upwards of 100%.



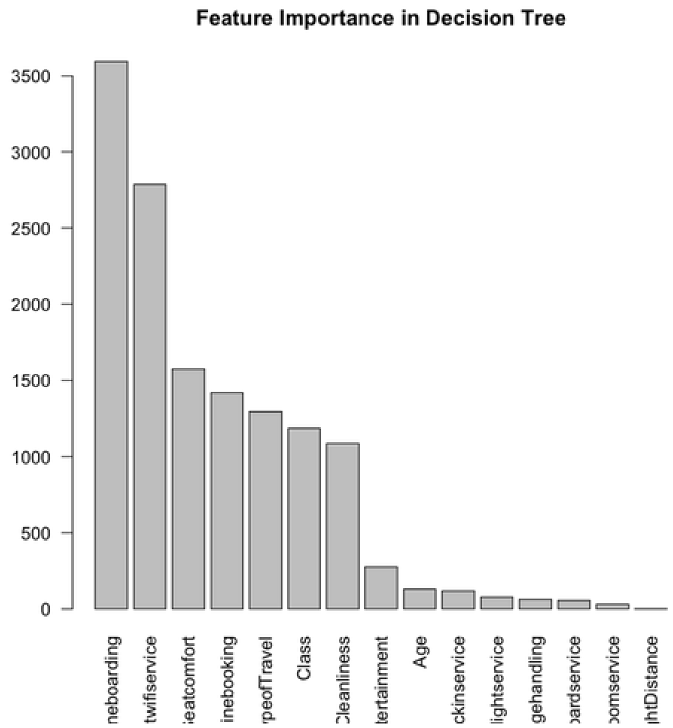
Plot showing the top 26 outliers, identified as outliers in all 41 iterations values of K..

The outliers that were identified were dealt with as detailed in section **4**.

3.4 Feature Significance

Feature significance analysis using decision trees found "OnlineBoarding" to be most significant, while "Legroomservice" to be of least significance. However, despite this, online boarding exhibits one of the more significant negative skews, indicating that, while it definitely has room for improvement, perhaps great return on investment would be gained from improving another service. For example, the second most significant feature was "Inflightwifiservice", which exhibits almost no skew - perhaps this should be an area of focus. The feature significance plot is shown below.

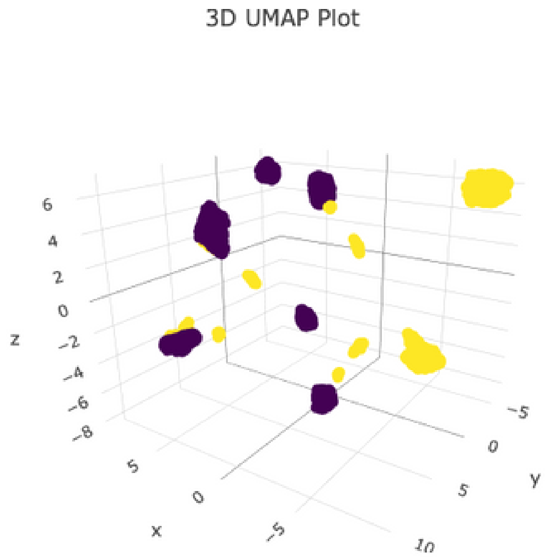
EDA & Preparation

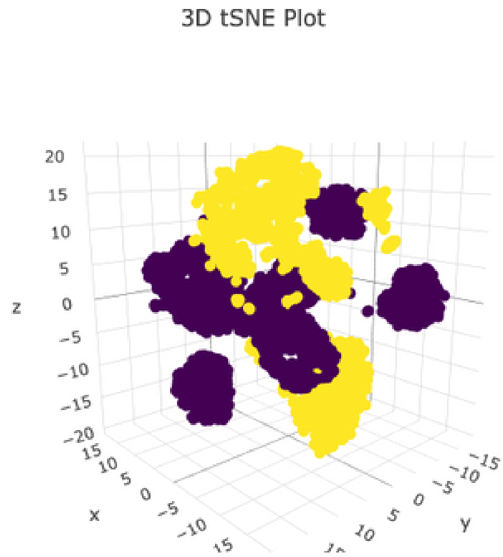


Feature signifcance plot of the nontrivially contributing features.

3.5 3D Visualisation

In our outlier analysis using LOF, a *K* value of 43 was used to identify the 22 outliers. Using this same value for parameters in a 3D Uniform Manifold Approximation & Projection (UMAP), *n_neighbours*, and a t-Distributed Stochastic Neighbour Embedding, *perplexity*, the following plots illustrate a uniformly sampled subset of the imputed data (due to resource constraints) of 20,000 samples. When coloured by the sample's Satisfaction value, there is extremely high separability.





20,000 uniformly sampled subset projected via UMAP (left) and tSNA (right) ito 3D, coloured by Satisfaction.

Data Preprocessing

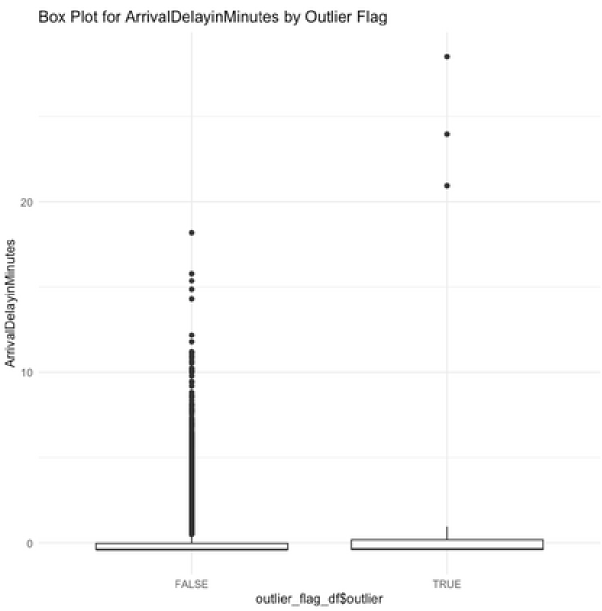
4.1 Feature Imputation

4.1.1 Missing Values

As previously mentioned, the missing values of "ArrivalDelayinMinutes", referenced in section **3,** were imputed via linear regression. The main feature used to make this prediction was "DepartureDelayinMinutes" due to it's high collinearity (0.965 Pearson's correlation coefficient) with the target variable. "FlightDistance", "TypeofTravel" and "CustomerType" all seemed to improve the predictive performance of the model. The performance metric used was Coefficient of Determination (CoD, R-squared), and the model achieved a maximum CoD value of ~0.93. The model was then used to predict the missing values of "ArrivalDelayinMinutes", which were then imputed using these values.

4.1.2 Outliers

After missing values were imputed, the data was standardised by z-score to preserve the intra-feature relationships and reduce the impact of the high skew of the delay-related features. The outliers were then analysed and it was shown to have detected the extremes of the continuous features. An example boxplot of the ArrivalDelayinMinutes feature illustrates this below.



Boxplot of ArrivalDelayinMinutes displaying outliers detected.

Since LOF detects sample-wise outliers rather than feature-wise outliers, these outliers will be removed. The resulting data will be compared against the data generated via standard imputation methods such as median imputation following from the chi-squared test for feature-wise anomalies, by comparing the performance of the classification models on the datasets.

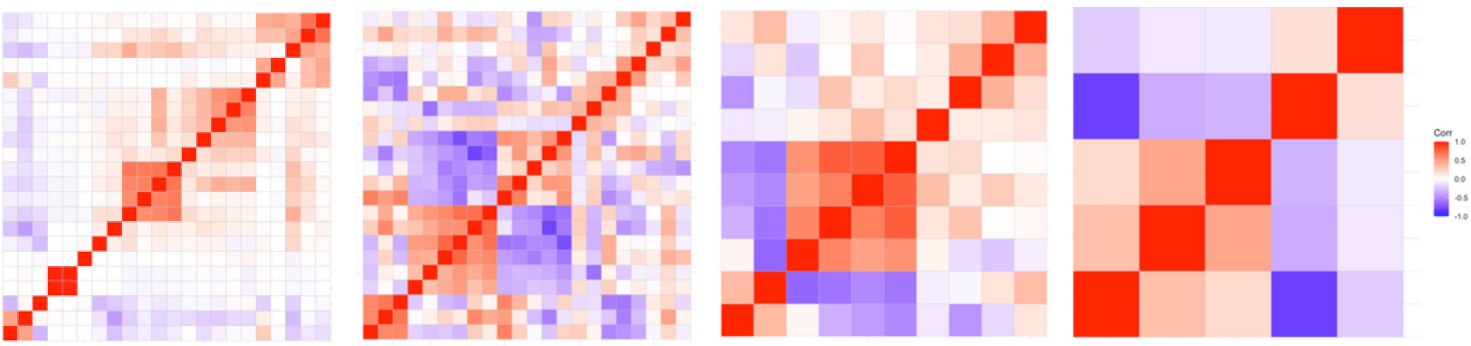
4.2 Dimensionality Reduction

Dimensionality reduction may be required (though not necessarily) due to the use of the 20,000 sample subset of the data, which reduces the sample-feature ratio to less than 1000. Due to the variety of the data being a mix of 1) continuous (time/distance features); 2) rank-ordered categorical (ratings features); 3) dichotomous binary categorical (gender, customer type, type of flight), correlation analysis is a significant and complex task, as a mix of correlation coefficients (Pearson's, Spearman's, Kendall's Tau) , contribution measures (Cramer's V) and Analysis of Variation (ANOV), among other techniques, would be required to gauge the full scope of relationships between features. A more straight forward approach is using an autoencoder to encode the features into a similar or lower dimensional latent space. This allows us to encode nonlinear relationships, as well as reduce all adequately encoded features down into a separable representation. Given that it's a continuous space, Pearson's or Spearman's coefficients can be used on the latent representation to analyse the correlation of the encoded features.

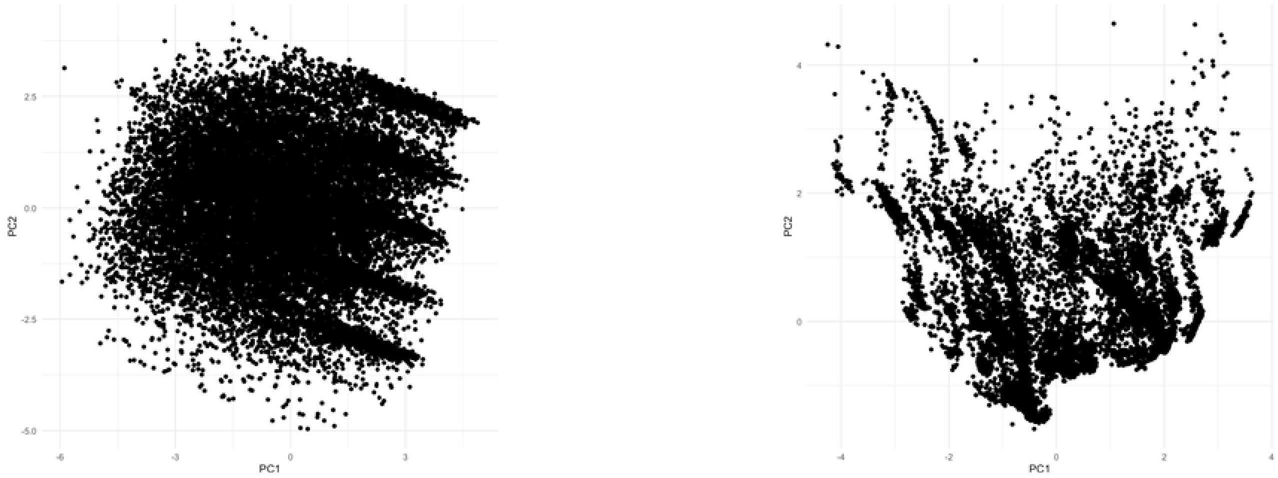
Another technique was previously already featured, which is UMAP and tSNE. As previously demonstrated, the projections produce highly separable embeddings of the data in even as low as 3 dimensions. This is likely due to the significance of a few features dominating over the rest. Autoencoder latent space analysis is shown below.

4.2.1 Autoencoder

Autoencoder embedding proved ineffective due to the difficulty in minimising the reconstruction error. 3 autoencoder architectures were applied, each with 3 layers with varying numbers of neurons depending on the size of the latent space that was being encoded to. The latent space sizes were 22 (a re-embedding of the same dimensionality), 10, and 5. Each layer used batch normalisation and ReLu activation functions, with the output layer of the decoder being a sigmoid activation function, and Mean Square Error was used as the loss function. Of the 3 models, of course, the one with the latent space of 22 neurons had the lowest MSE output on both training and test sets. Despite this, all encodings seemed to generate embeddings with increase Pearson's correlation coefficients when compared to an (purely **illustrative**) correlation matrix of the original data, rendering them useless. The following plots depict their correlation and visualisations of their first 2 principle components. Plots of proportion of variance explained is included only for the data encoded by the 10-neuron autoencoder for illustrative purposes, as they were not useful

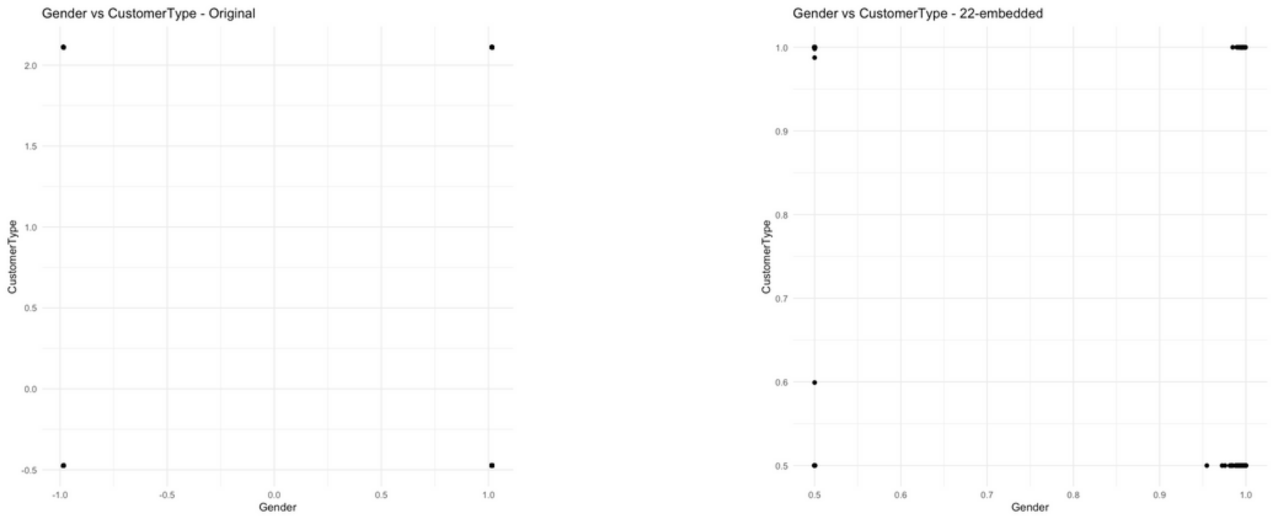


Pearson's correlation heatmaps of orginal (left), 22 (second), 10 (third), 5 (right) embedded feature embeddings.



Principal Component 1 and 2 of the original (left) data and the 22-dimension encoded (right) data.

The following plots of the first 2 features of the original data (left) and the 22-dimension encoded data (right) show that there is a nontrivial reconstruction error that is not addressed, despite no reduction in the latent space.



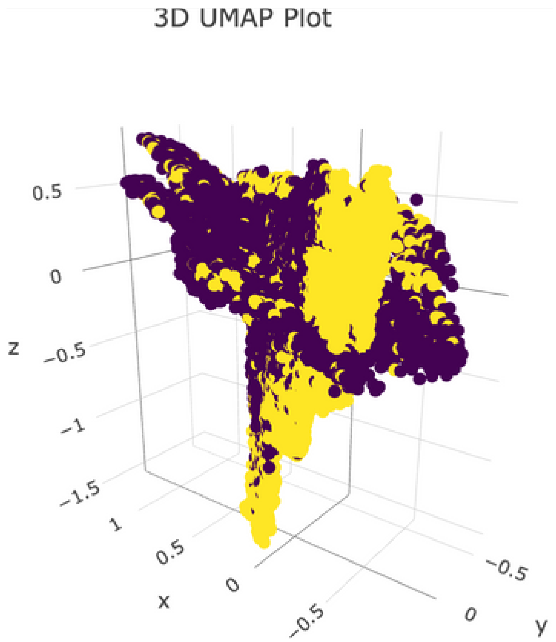
Gender-CustomerType plot of original (left) data and 22-dimension encoded (right) data.

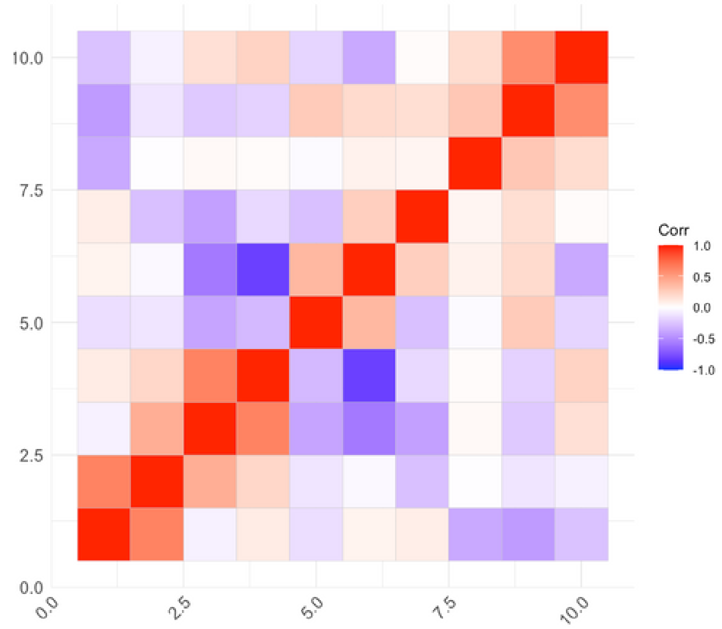
Despite both variables being binary categorical, the plot on the right shows characteristics of continuity in both Gender and CustomerType features, that is, variance about one of the gender values, as well as variance about one of the CustomerType values. Perhaps further extensive investigation could yield better results, but this is out of the scope of this project, so we proceed with UMAP.

4.2.2 UMAP Reduction

The following plots show the Pearson’s correlation heatmap for the reduction of the original data to 10 dimensions using the same parameters as previously stated.

Preprocessing





3D plot of first 3 components of 10D UMAP reduction coloured by satisfaction (left), and correlation heatmap (right).

In comparison to the correlation heatmap produced by the autoencoder encoding the data into 10D, this one shows more feature-wise independence in the data. A comparison of all techniques will be required to test the efficacy of the three data set - the original, the auto-encoder reduced 10D data, and the UMAP reduced 10D data.

Modelling & Metrics

5.1 Deep Neural Network - Ali

5.1.1 Architecture

Three different model architectures were tested - 1 for the original data of 22 features, and 2 for the autoencoder and umap embedded data of 10 features each. The model for the original data consisted of 6 layers, batch normalisation, ReLU activation, a dropout layer with 30% probability, and a sigmoid activation acting on a single output neuron at the output layer. The only change made to the other 2 models is that the number of layers was reduced from 6 to 5 and 4 respectively to reduce model complexity and reduce overfitting.

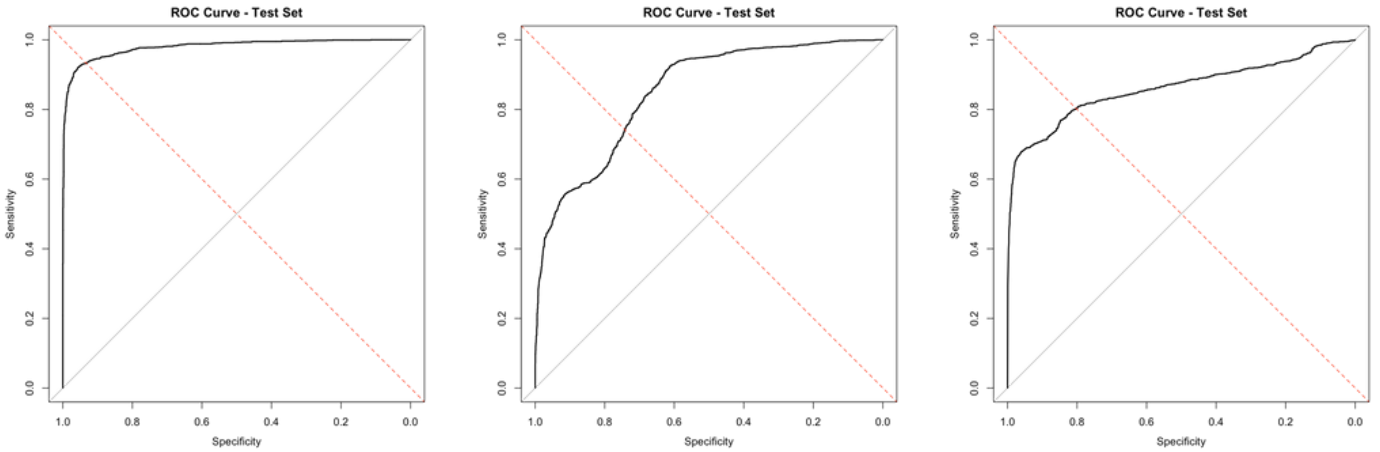
5.1.2 Data Preparation & Regularisation

Prior to input, the data was split into stratified train and tests subsets. Both subsets were standardised using the z-scale metrics of the train subset to avoid data leakage. The train subset was then split again used stratified k-fold cross-validation, with 5 validation folds, in order to further prevent overfitting. This new train-validation split was also standardised using the z-scale metrics of this new train set, to prevent data leakage. All partitioning occurred with an 80/20 split.

Both dropout and k-fold cross-validation aided in preventing overfitting. Unfortunately, due to resource constraints (Tensorflow/Keras incompatibility with Silicon Macs meant using PyTorch, which has no GridSearchCV implementation), hyperparameter tuning was not available via Grid Search. Instead, empirical testing was used to obtain optimal hyper parameters.

5.1.3 Results & Performance Metrics

Needless to say, the model performing on the original feature data, with 22 features, performed the best by far. It achieved a test accuracy of 94.05%. Ultimately, only the 2nd model architecture was used for both the UMAP embedded data and the Autoencoder embedded data. It achieved 49.75% and 73.13% accuracy, respectively. The rest of the performance metrics are visualised below.




```
F1 Score on Test Set:  0.9302462
AUC Score on Test Set:  0.9798388
```

```
F1 Score on Test Set:  0.7490077
AUC Score on Test Set:  0.8498503
```

```
F1 Score on Test Set:  0.6203249
AUC Score on Test Set:  0.8614799
```

F1 score and AUC for the original feature data (left), Autencoder data (middle), and UMAP data (right).

The data shows that the model which classified the original feature data is exceptionally performant, given that the ROC-AUC is ~0.98 which shows that it has an extremely low false positive rate and very high sensitivity. Coupled with its 94.05% accuracy on the test set, there is strong indication that it is almost ideal. The F1-score of ~0.93 shows that it has exceptional ability to differentiate between classes while also remaining sensitive to them.

The curves of the other 2 datasets are interesting; in the case of the UMAP data, which performed the worst in terms of accuracy at 49.75%, it still maintained a relatively high AUC of ~0.86. This seems to conflict with its harmonic mean of ~0.62 and may be worth investigating. The Autoencoder dataset exhibits a similar AUC as the UMAP data, at ~0.85, but as expected, its F1-score is higher, at ~0.75, matching its accuracy of 73.13%. Perhaps further investigation into the encoding process, or encoding to a high dimensional space, like 15D, may produce better results as it reduces the reconstruction error and distorts the statistical properties of the data much less.

5.2 Support Vector Machine - Ali

5.2.1 Data Preparation & Regularisation

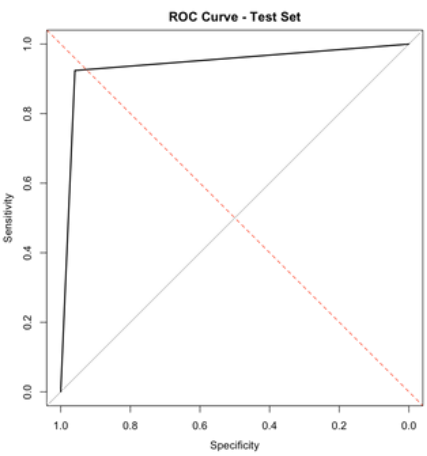
The data was prepared identically to that which was prepared for DNN classification.

5.2.2 Architecture

Empirical testing showed a Radial Basis Function/Gaussian kernel to perform best. Standard cost & gamma parameters were used.

5.2.3 Results & Performance Metrics

Given the significant difference in performance of the DNN between datasets, only the original features were used for the SVM. The SVM outperformed the DNN, with a test accuracy of 94.35%. Interestingly, the F1 score was unbalanced. The plots below show the key performance metrics.



	Actual	
Predicted	0	1
0	2134	135
1	91	1640

```
F1 Score on Test Set:  0.1123128
AUC Score on Test Set:  0.9415224
```

ROC for the original data (left), F1 & AUC (lower), and Confusion Matrix (right) for SVM on original features..

Conclusion & Recommendation

Conclusion

Models

This data shows that, while it the SVM was more performant in the accuracy metric, it was only marginally better. On the other hand, the combination of its significantly worse performance in the F1 metric, as well as its marginally worse AUC value, indicate that perhaps the DNN is a better choice over it for classification. However, there is further scope for investigation with grid search in the Autoencoder, the DNN and SVM models in order to extract optimal feature representations and performance. Further, UMAP and tSNE proved to be ineffective techniques for dimensionality reduction. UMAP was slightly more suitable given the mathematical logic of tSNE being stochastic projections onto less dimensions using t-distributions - in the case of UMAP, the gradient descent over its cost function (similarity differences) provides a mathematically more stable and consistent result for embedding, though trivially so.

Recommendations

Recommendations to senior management on the technical process include the following:

- Further investigation into feature importance and factor analysis to identify consistently highly contributing features;
- Further investigation into hyper parameter tuning for even more accurate models using grid search, and for the derivation of a new, more concentrated feature space;

Recommendations to senior management on the business problem of understanding and improvig the factors driving customer satisfaction includes focusing on the features with both the most positive skew and simultaneously highest importance. In particular:

- Inflight wifi service was identified as the 2nd most important factor, yet it was the only feature with positive skew. The belief is that efficient allocation of capital and resources includes investing in and improving the inflight wifi service, as it is likely to generate the great improvement in satisfaction for given unit of currency or other resource.
- Ease of online booking was identified as the 4th most important feature, with approximately similar importance to inflight wifi service, yet it has the 2nd most positive skew (or least negative, at -0.2). Similarly, investing in this **after** the inflight wifi service would be the best use of company capital and resources. Improvements are dependant on further qualitative analysis of the exact issues and frustrations faced by the customers.

Lastly, it seems that the majority of neutrality or dissatisfaction seems to be approximately equally distributed (save for the 2 most important features mentioned earlier) among the rest of the services. Further, analysis of the distributions of flight-type against satisfaction showed that business-class customers seemed to be least neutral or dissatisfied, intuitively. Economy customers were the most neutral or dissatisfied, closely followed by Economy Plus, indicating that allocation of resources should be focused in the Economy flight class. Given that the vast majority of customers fly Economy, this would likely generate the greatest return on investment, in terms of profit, customer satisfaction rating and likely competitive advantage index.

Contributions

This report was produced entirely by Ali Shihab, URN6564898. All work, code, plots and data generated was the result of Ali Shihab's work alone. Due to the lack of collaboration and input from the rest of the group, contributions from them were not able to be obtained in time before submission.

This is also the case for the presentation, where only the basic points of slides 3, 4 and 9 were not produced (but still edited or guided) by Ali.