DABI Assignment 2

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Introduction & Objectives

Airbnb Inc. is an American company based in San Francisco, California that was founded in 2008 by Brian Chesky, Nathan Blecharczyk and Joe Gebbia. Airbnb is a shortened version of the original name, AirBedandBreakfast. The company operates an online marketplace for vacation rentals which are typically homestays. The company generates revenue by collecting a commission from each booking that is made on its platforms. As such, it does not own any of the properties that are listed for booking.

This dataset contains data 7323 rows and 106 columns of various properties listed in Singapore over the past few years.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7323 entries, 0 to 7322
Data columns (total 106 columns):
 #   Column                                        Non-Null Count  Dtype
---  ------                                        --------------  -----
 0   id                                            7323 non-null   int64
 1   listing_url                                   7323 non-null   object
 2   scrape_id                                     7323 non-null   float64
 3   last_scraped                                  7323 non-null   int64
 4   name                                          7319 non-null   object
 5   summary                                       6964 non-null   object
```

Using the data provided, the study aims to build a classification model to identify the listings that will be popular. The insights gained can hopefully then be used to determine what contribute to the popularity of the more popular listings and help the less popular listings improve.

Data Exploration & Preparation

Most of the data exploration and preparation was done in a Jupyter Notebook.

Columns with large number of null values were dropped followed by columns containing ID, name, URL and date.

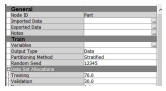
Categorical columns with too many unique values or only one unique value were dropped. Categorical columns with an overwhelming majority in a single class were also dropped.

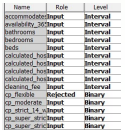
Checking the correlation between each of the numerical columns, those with high collinearity were dropped.

Dummy variables were created for the remaining categorical features.

All rows containing null values were dropped.

The final dataset of 2605 rows and 48 columns were exported as a csv and imported into SAS. All the dummy variables were changed to “binary” type. One dummy was also set to “rejected” from each group. (e.g. host is superhost. A “1” on the “false” dummy variable is the same as a “0” on the “true” variable and thus unnecessary) A quick exploration of the imported data reveals an outlier in the maximum nights feature which was removed by a filter node.

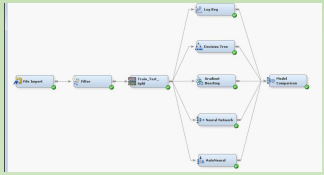




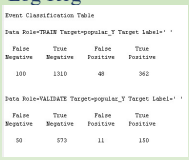
A partition was created to split the dataset between train and validation data in a 70-30 ratio stratified.

Workflow

The diagram used contains the import, filter and partition nodes, as well as various classification models and a comparison node. The configuration for the diagram is below and the models were all run based on default configurations with the results as follows:

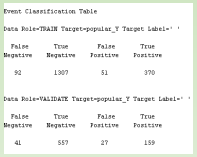


Log Reg



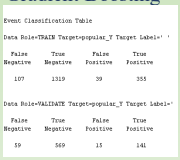
```
Event Classification Table

Data Role=TRAIN Target=popular_Y Target Label=' '

 False      True       False      True
 Negative   Negative   Positive   Positive
 100        1310       48         362

Data Role=VALIDATE Target=popular_Y Target Label=' '

 False      True       False      True
 Negative   Negative   Positive   Positive
 50         573        11         150
```

Decision Tree



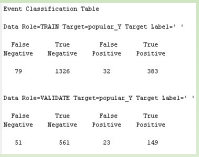
```
Event Classification Table

Data Role=TRAIN Target=popular_Y Target Label=' '

 False      True       False      True
 Negative   Negative   Positive   Positive
 92         1307       51         370

Data Role=VALIDATE Target=popular_Y Target Label=' '

 False      True       False      True
 Negative   Negative   Positive   Positive
 41         557        27         159
```

Gradient Boosting



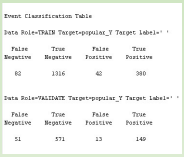
```
Event Classification Table

Data Role=TRAIN Target=popular_Y Target Label=' '

 False      True       False      True
 Negative   Negative   Positive   Positive
 107        1319       39         355

Data Role=VALIDATE Target=popular_Y Target Label=' '

 False      True       False      True
 Negative   Negative   Positive   Positive
 59         569        15         141
```

Neural Network



```
Event Classification Table

Data Role=TRAIN Target=popular_Y Target Label=' '

 False      True       False      True
 Negative   Negative   Positive   Positive
 79         1326       32         383

Data Role=VALIDATE Target=popular_Y Target Label=' '

 False      True       False      True
 Negative   Negative   Positive   Positive
 51         561        23         149
```

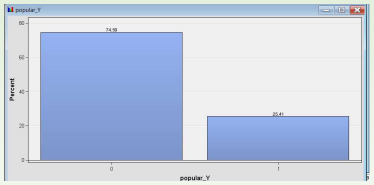
AutoNeural



```
Event Classification Table

Data Role=TRAIN Target=popular_Y Target Label=' '

 False      True       False      True
 Negative   Negative   Positive   Positive
 82         1316       42         380

Data Role=VALIDATE Target=popular_Y Target Label=' '

 False      True       False      True
 Negative   Negative   Positive   Positive
 51         571        13         140
```

Findings and Recommendations

As such, the model comparison module was set to select the best performing model based on misclassification. However, due to a class imbalance, misclassification may not be the best metric.



Fit Statistics

Selected Model	Predecessor Node	Model Node	Model Description	Target Variable	Target Label	Selection Criterion: Valid: Misclassification
Y	Reg	Reg	Log Reg	popular	Y	0.077806
	AutoNeural	AutoNeural	AutoNeural	popular	Y	0.081633
	Tree	Tree	Decision ...	popular	Y	0.086735
	Boost	Boost	Gradient ...	popular	Y	0.094388
	Neural	Neural	Neural N...	popular	Y	0.094388

Target Label

Instead, F1 score is calculated:

Logistic Regression	Decision Tree	Gradient Boosting	Neural Network	AutoNeural
0.831	0.824	0.792	0.801	0.823

The best performing model is still Logistic Regression. A possible way to improve the model may be to SMOTE after the partition before modelling but that will not be covered within this project.

Examining the feature weight importance of the logistic regression, we are able to identify that the following are the top 10 features that are important in determining popularity:

Latitude, Host Response Rate, Host Acceptance Rate, Number of Bathrooms, Moderate Strictness on Cancellations, Review Scores, Room Type, Bedrooms, whether the host is a SuperHost and Number of Guests included.

Based on the features identified, some cannot be changed such as the Latitude and Number of Bathrooms and Bedrooms. Nonetheless, the opportunities for improvement are available, such as, Responding to and Accepting more Booking Requests, and Trying not to be too Strict on Cancellations which should also increase their Review Scores.