IST 707 FINAL PROJECT

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Data Pre-processing/Data Preparation Phase

Phase 1: Mitigate Missing Data

The original AirlineData.xlsx dataset required munging and preprocessing before it could be prepared for analysis. Our team utilized Jupyter Notebooks to perform this phase. The dataset was read in using the pd.read_excel() function from the Pandas package in Python. Pandas is a fast, powerful, flexible and easy to use open source data analysis and manipulation tool. The dataset was read in as the airline data frame. The data frame was initially analyzed using the airline.info() and airline.describe() functions. There were several columns in the data frame that may have contained missing data. The function airline.isna().sum() was used to determine the location of missing data. There were 323 missing values not including the freeText attribute from Departure.Delay.in.Minutes (99), Arrival.Delay.in.Minutes (112), and Flight.time.in.minutes (112). The freeText attribute was then dropped to simplify dealing with the true missing data using the airline.drop() function. A new data frame of missing values named null_data was created using a reset index. This was done by using null_data = airline[df.isnull().any(axis=1)].reset_index(). It was then discovered that many missing values were found where a flight cancellation occurred. By using airline.loc[airline["Flight.cancelled"]=='Yes'] it was determined that 101 records with this criterion contained missing values. Because the flight never occurred, all of the records that had missing values with this criterion were replaced with 0 for the Departure.Delay.in.Minutes, Arrival.Delay.in.Minutes, and Flight.time.in.minutes attributes. This was done using airline.loc[airline['Flight.cancelled'] == 'Yes', 'Departure.Delay.in.Minutes'] = 0 where the second argument was the name of the respective missing attribute. The remaining missing values were replaced with the mean of their respective attributes using airline['Departure.Delay.in.Minutes'].fillna((airline['Departure.Delay.in.Minutes'].mean()), inplace=True) again using the name of the respective missing attribute. It was determined that the best way to replace the NA values was by mean substitution as the missing values in the columns was less than 5% of the total dataset.

Phase 2: Summarize Variables

After missing data was mitigated, initial variable summarization was carried out in the Jupyter Notebook before further variable summarization was completed in the Orange Workflow. Histograms for each attribute were created using the px.histogram() function from the Plotly Express package in Python. Plotly Express is a high-level Python visualization library. The Age attribute had a symmetric distribution. Likelihood.to.recommend attribute was negatively skewed. All other numeric variables were positively skewed. This included Price.Sensitivity, Flights.Per.Year, Loyalty, Total.Freq.Flyer.Accts, Departure.Delay.in.Minutes, Arrival.Delay.in.Minutes, Flight.Distance, and Flight.time.in.minutes.

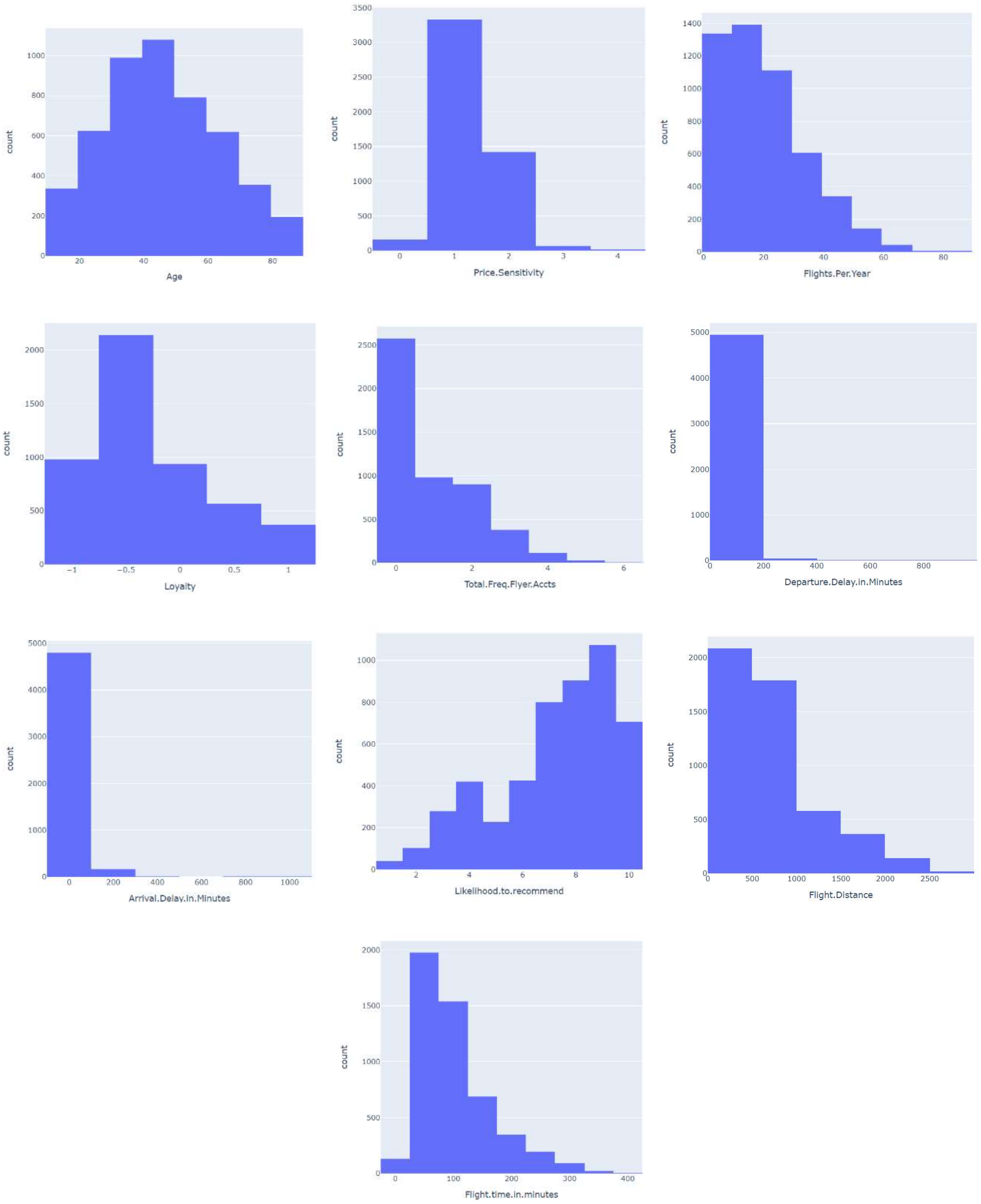
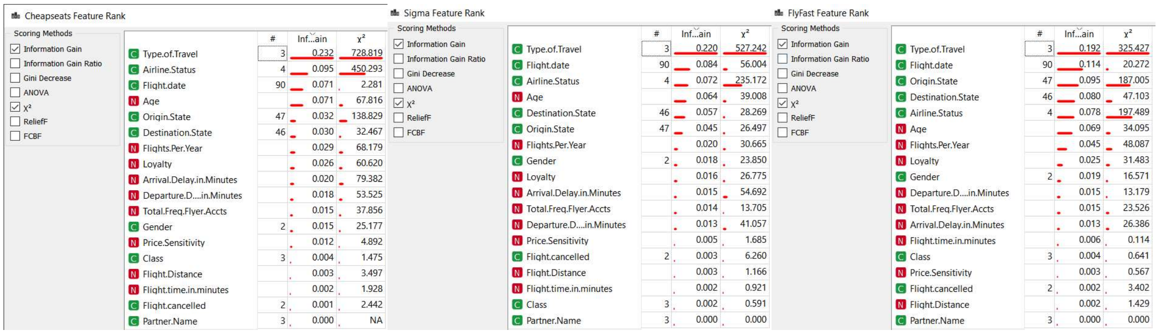


Figure 1: Numeric variable histogram distributions

The final cleaned data frame was exported to excel using the airline.to_excel() function. This file was then read in as new.xlsx into the Orange Workflow. Data was separated according to each airline. Cheapseats, Sigma, and FlyFast. For accurate feature ranking the Likelihood.to.recommend attribute was removed from the data frame. Information Gain and Correlation (X^2) was used to rank important attributes. Type.of.Travel, Airline.Status, and Flight.date were consistently at the top for the higher performing airlines Cheapseats and Sigma. Origin.State and Destination.State attributes were also high ranking for FlyFast.



Cheapseats Feature Rank

Scoring Methods
☑ Information Gain
☐ Information Gain Ratio
☐ Gini Decrease
☐ ANOVA
☑ χ²
☐ ReliefF
☐ FCBF

	#	Inf...ain	χ²
C Type.of.Travel	3	0.232	728.819
C Airline.Status	4	0.095	450.293
C Flight.date	90	0.071	2.281
N Age		0.071	67.816
C Origin.State	47	0.032	138.829
C Destination.State	46	0.030	32.467
N Flights.Per.Year		0.029	68.179
N Loyalty		0.026	60.620
N Arrival.Delay.in.Minutes		0.020	79.382
N Departure.D....in.Minutes		0.018	53.525
N Total.Freq.Flyer.Accts		0.015	37.856
C Gender	2	0.015	25.177
N Price.Sensitivity		0.012	4.892
C Class	3	0.004	1.475
N Flight.Distance		0.003	3.497
N Flight.time.in.minutes		0.002	1.928
C Flight.cancelled	2	0.001	2.442
C Partner.Name	3	0.000	NA

Sigma Feature Rank

Scoring Methods
☑ Information Gain
☐ Information Gain Ratio
☐ Gini Decrease
☐ ANOVA
☑ χ²
☐ ReliefF
☐ FCBF

	#	Inf...ain	χ²
C Type.of.Travel	3	0.220	527.242
C Flight.date	90	0.084	56.004
C Airline.Status	4	0.072	235.172
N Age		0.064	39.008
C Destination.State	46	0.057	28.269
C Origin.State	47	0.045	26.497
N Flights.Per.Year		0.020	30.665
C Gender	2	0.018	23.850
N Loyalty		0.016	26.775
N Arrival.Delay.in.Minutes		0.015	54.692
N Total.Freq.Flyer.Accts		0.014	13.705
N Departure.D....in.Minutes		0.013	41.057
N Price.Sensitivity		0.005	1.685
C Flight.cancelled	2	0.003	6.260
N Flight.Distance		0.003	1.166
N Flight.time.in.minutes		0.002	0.921
C Class	3	0.002	0.591
C Partner.Name	3	0.000	0.000

FlyFast Feature Rank

Scoring Methods
☑ Information Gain
☐ Information Gain Ratio
☐ Gini Decrease
☐ ANOVA
☑ χ²
☐ ReliefF
☐ FCBF

	#	Inf...ain	χ²
C Type.of.Travel	3	0.192	325.427
C Flight.date	90	0.114	20.272
C Origin.State	47	0.095	187.005
C Destination.State	46	0.080	47.103
C Airline.Status	4	0.078	197.489
N Age		0.069	34.095
N Flights.Per.Year		0.045	48.087
N Loyalty		0.025	31.483
C Gender	2	0.019	16.571
N Departure.D....in.Minutes		0.015	13.179
N Total.Freq.Flyer.Accts		0.015	23.526
N Arrival.Delay.in.Minutes		0.013	26.386
N Flight.time.in.minutes		0.006	0.114
C Class	3	0.004	0.641
N Price.Sensitivity		0.003	0.567
C Flight.cancelled	2	0.002	3.402
N Flight.Distance		0.002	1.429
C Partner.Name	3	0.000	0.000

Figure 2: Feature ranking results for all three airlines

Histograms were then created for each airline highlighting the variable distributions. Box plots and feature statistics were also enlisted to assist in summarizing variables.

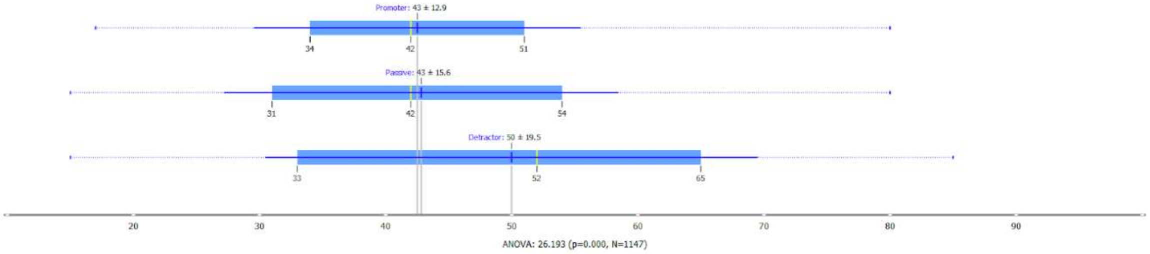


Figure 3: Box plot example for the Age attribute separated by category

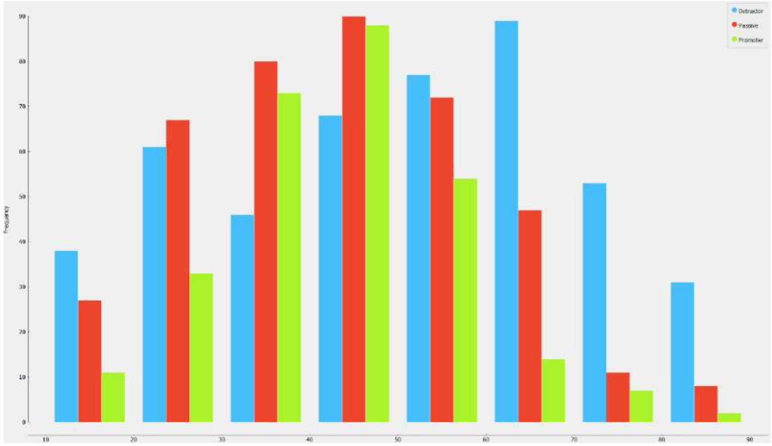
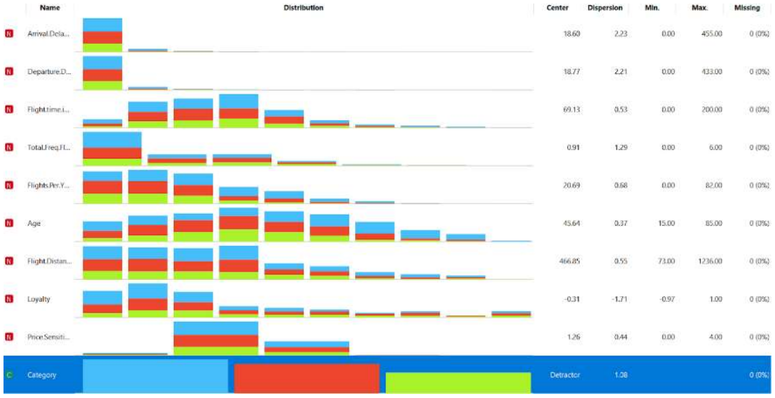


Figure 4: Histogram example for the Age attribute separated by category



	Name	Distribution	Center	Dispersion	Min.	Max.	Missing
N	Arrival.Dela...		18.60	2.23	0.00	455.00	0 (0%)
N	Departure.D...		18.77	2.21	0.00	433.00	0 (0%)
N	Flight.time.i...		69.13	0.53	0.00	200.00	0 (0%)
N	Total.Freq.Fl...		0.91	1.29	0.00	6.00	0 (0%)
N	Flights.Per.Y...		20.69	0.68	0.00	82.00	0 (0%)
N	Age		45.64	0.37	15.00	85.00	0 (0%)
N	Flight.Distan...		466.85	0.55	73.00	1236.00	0 (0%)
N	Loyalty		-0.31	-1.71	-0.97	1.00	0 (0%)
N	Price.Sensiti...		1.26	0.44	0.00	4.00	0 (0%)
C	Category		Detractor	1.08			0 (0%)

Figure 5: Feature statistics for FlyFast numeric variables

The same technique was then carried out after discretizing variables into appropriate binnings. Age, Flights.Per.Year, Likelihood.to.recommend, Flight.Distance, and Flight.time.in.minutes attributes used 10 bins. Price.Sensitivity, Loyalty, Departure.Delay.in.Minutes, and Arrival.Delay.in.Minutes attributes used 5 bins. The Total.Freq.Flyer.Accts used 7 bins.

Exploratory Analysis Phase

Phase 3: Segment Your Population

Our team utilized undirected data mining techniques to identify an interesting segment of people in each of the 3 NPS categories (Detractors, Passives, Promoters). This was done through a combination of K-means Clustering Analysis, manual clustering, and Associated Rules Mining in the Orange Workflow. Our team first attempted to generate useful segments through K-means Clustering Analysis. Unfortunately, there really was too much noise in the dataset leading to clusters that were difficult to interpret.

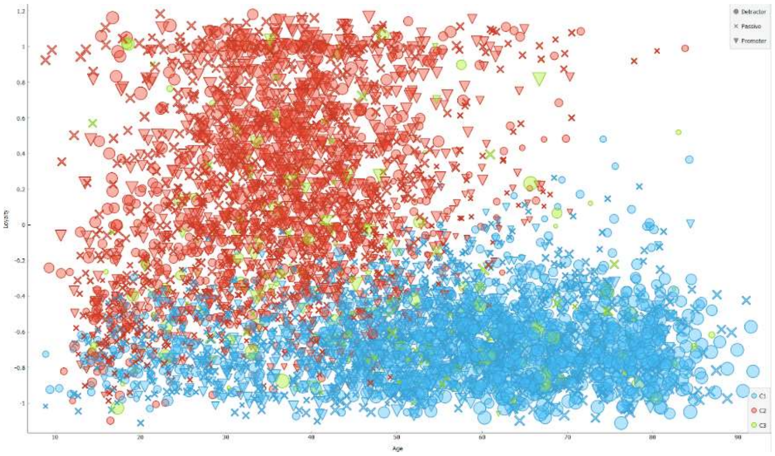


Figure 6: K-means clustering analysis output using the Age variable

This led to an attempt at manual clustering performed by using the predictions data from predictive model output. Manually filtering and aggregation allowed for building some more reliable clusters for identifying an interesting segment of people in each of the 3 NPS categories (Detractors, Passives, Promoters). These clusters were validated through rules found by running an Associated Rules Mining algorithm for each segment. FlyFast airline customers included a large demographic range of customers who were detractors, a fewer number of passives, and an even smaller number of promoters. A generic persona of promoters for both Sigma and Cheapseats airlines were created to help identify what made passengers promoters. These personas will be revisited in-depth during phase 7: Develop Marketing Plan.

Supp	Conf	Covr	Strg	Lift	Levr	Antecedent		
0.027	0.806	0.034	8.806	2.684	0.017	Type.of.Travel=Personal Travel, Airline.Status=Blue, Age=55 - 65, Total.Freq.Flyer.Accts=< 1	→	Category=Detractor
0.031	0.783	0.040	7.561	2.607	0.019	Type.of.Travel=Personal Travel, Airline.Status=Blue, Age=55 - 65	→	Category=Detractor
0.024	0.764	0.031	9.535	2.545	0.015	Type.of.Travel=Personal Travel, Airline.Status=Blue, Age=≥ 75, Price.Sensitivity=1 - 2	→	Category=Detractor
0.023	0.760	0.031	9.721	2.530	0.014	Type.of.Travel=Personal Travel, Airline.Status=Blue, Age=≥ 75, Total.Freq.Flyer.Accts=< 1, Price.Sensitivity=1 - 2	→	Category=Detractor
0.021	0.757	0.027	11.007	2.522	0.012	Type.of.Travel=Personal Travel, Airline.Status=Blue, Age=55 - 65, Price.Sensitivity=1 - 2	→	Category=Detractor
0.025	0.755	0.033	9.184	2.513	0.015	Type.of.Travel=Personal Travel, Airline.Status=Blue, Age=65 - 75, Gender=Female	→	Category=Detractor
0.024	0.748	0.033	9.184	2.492	0.015	Type.of.Travel=Personal Travel, Airline.Status=Blue, Age=≥ 75, Gender=Female	→	Category=Detractor
0.023	0.747	0.031	9.721	2.487	0.014	Type.of.Travel=Personal Travel, Airline.Status=Blue, Age=65 - 75, Gender=Female, Total.Freq.Flyer.Accts=< 1	→	Category=Detractor
0.024	0.744	0.032	9.356	2.477	0.014	Type.of.Travel=Personal Travel, Airline.Status=Blue, Age=≥ 75, Gender=Female, Total.Freq.Flyer.Accts=< 1	→	Category=Detractor
0.035	0.743	0.048	6.316	2.473	0.021	Type.of.Travel=Personal Travel, Airline.Status=Blue, Age=65 - 75	→	Category=Detractor

Figure 7: Associated Rules Mining output for detractors

Supp	Conf	Covr	Strg	Lift	Levr	Antecedent		
0.032	0.492	0.066	5.188	1.438	0.010	Type.of.Travel=Mileage tickets, Airline.Status=Blue	→	Category=Passive
0.031	0.465	0.067	5.126	1.359	0.008	Age=< 25, Arrival.Delay.in.Minutes=< 0.5	→	Category=Passive
0.047	0.426	0.111	3.081	1.244	0.009	Airline.Status=Blue, Age=< 25	→	Category=Passive
0.034	0.424	0.079	4.332	1.238	0.006	Type.of.Travel=Business travel, Airline.Status=Blue, Age=25 - 35	→	Category=Passive
0.044	0.406	0.108	3.167	1.187	0.007	Airline.Status=Blue, Age=25 - 35	→	Category=Passive
0.040	0.389	0.102	3.374	1.137	0.005	Age=25 - 35, Gender=Female	→	Category=Passive
0.032	0.381	0.085	4.035	1.112	0.003	Type.of.Travel=Business travel, Age=25 - 35, Price.Sensitivity=1 - 2	→	Category=Passive
0.042	0.379	0.110	3.109	1.106	0.004	Age=25 - 35, Price.Sensitivity=1 - 2	→	Category=Passive
0.032	0.377	0.084	4.074	1.101	0.003	Age=25 - 35, Departure.Delay.in.Minutes=< 0	→	Category=Passive
0.033	0.371	0.089	3.862	1.084	0.003	Type.of.Travel=Business travel, Airline.Status=Blue, Age=45 - 55	→	Category=Passive

Figure 8: Associated Rules Mining output for passives

Supp	Conf	Covr	Strg	Lift	Levr	Antecedent		
0.052	0.648	0.080	4.475	1.814	0.023	Type.of.Travel=Business travel, Age=35 - 45, Gender=Male	→	Category=Promoter
0.045	0.642	0.070	5.103	1.796	0.020	Age=35 - 45, Gender=Male, Price.Sensitivity=1 - 2	→	Category=Promoter
0.041	0.622	0.066	5.430	1.741	0.017	Type.of.Travel=Business travel, Age=35 - 45, Arrival.Delay.in.Minutes=< 0.5, Price.Sensitivity=1 - 2	→	Category=Promoter
0.058	0.610	0.095	3.757	1.707	0.024	Age=35 - 45, Gender=Male	→	Category=Promoter
0.045	0.603	0.074	4.840	1.689	0.018	Type.of.Travel=Business travel, Age=45 - 55, Arrival.Delay.in.Minutes=< 0.5	→	Category=Promoter
0.043	0.601	0.072	4.975	1.681	0.017	Type.of.Travel=Business travel, Age=45 - 55, Departure.Delay.in.Minutes=< 0	→	Category=Promoter
0.041	0.590	0.070	5.103	1.652	0.016	Type.of.Travel=Business travel, Age=45 - 55, Gender=Male	→	Category=Promoter
0.052	0.588	0.088	4.076	1.646	0.020	Type.of.Travel=Business travel, Age=35 - 45, Arrival.Delay.in.Minutes=< 0.5	→	Category=Promoter
0.049	0.587	0.084	4.251	1.643	0.019	Type.of.Travel=Business travel, Age=35 - 45, Departure.Delay.in.Minutes=< 0	→	Category=Promoter
0.041	0.585	0.071	5.060	1.638	0.016	Type.of.Travel=Business travel, Age=35 - 45, Arrival.Delay.in.Minutes=< 0.5, Departure.Delay.in.Minutes=< 0	→	Category=Promoter

Figure 9: Associated Rules Mining output for promoters

Phase 4: Sentiment Analysis

A text analysis was performed on 101 text records in order to identify customer sentiment. These surveys were isolated from FlyFast in order to perform both sentence and text level analysis. Once a word corpus was created, stop words and regular expressions were removed prior to using the Liu Hu Analysis method. After text preprocessing occurred, the output of the sentiment analysis was a corpus viewer for sentences and word clouds developed to identify key themes associated with positive and negative sentiment on the word level. Positive and negative sentiment were separated based on the sentiment metric. For the sentence level, high sentiment was above 2.5 and low sentiment was below 2.5. For the word level, high sentiment was above 0 while low sentiment was below 0. The key themes associated with negative sentiment included issues with luggage, food and drink quality, and seat comfortability. Price sensitive customers also complained about a pricing policy that charged customers extra for choosing where they sat.

Figure 10: Negative sentiment word cloud

The key themes associated with positive sentiment, though few and far between, included a friendly flight staff, operational services, and decent business class experience.

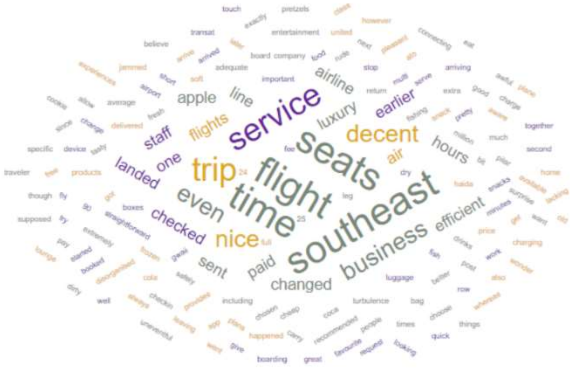


Figure 11: Positive sentiment word cloud

Phase 5: Predictive Modeling

Following the initial market segmentation and sentiment analysis, our team generated three different predictive models using Random Forest, Support Vector Machine, and Neural Network data mining techniques. These were first carried out in a Jupyter Notebook and then replicated for the Orange Workflow. The Support Vector Machine and Neural Network techniques required for the data to be in numeric form before fitting each model, if done manually. The 3 NPS categories (Detractors, Passives, Promoters) were converted to numeric form (1, 2, 3) by using airline['Category'].replace('Detractor', 1, inplace=True) for each respective category. The new numerized Category attribute was then stored as a separate vector named target. The Category attribute was then removed from the airline data frame. All other categorical variables in the data set were converted to numeric using the same method. Variables with several different strings were converted into numeric form using airline['Origin.State'] = airline['Origin.State'].astype('category').cat.rename_categories(range(1, airline['Origin.State'].nunique()+1)) for each unique value. The final data frame was exported as a comma delimited file named numerized.csv.

The Support Vector Machine required use of the Scikit-learn package which features various classification, regression, and clustering algorithms. Using the train_test_split() function we made a 70/30 split for the airline data frame. We used a radial basis function kernel as opposed to a linear kernel or polynomial using svm.SVC(kernel='rbf') as this seemed to produce the highest accuracy. A MinMaxScaler was utilized to minimize the amount of time taken to compute the model. The model was then fit using clf.fit(X_train, y_train) and predictions were made on the test data set. Accuracy for this model was reported at 98.40%.

The Keras package is TensorFlow's API for building and training deep learning models. This is what our team used for creating a Neural Network. Below is the baseline model where X = the airline data frame and Y = the target vector:

```
def baseline_model():
    # Create Model
    model = Sequential()
    model.add(Dense(8, input_dim=21, activation='relu'))
    model.add(Dense(3, activation='softmax'))
    # Compile Model
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model
```

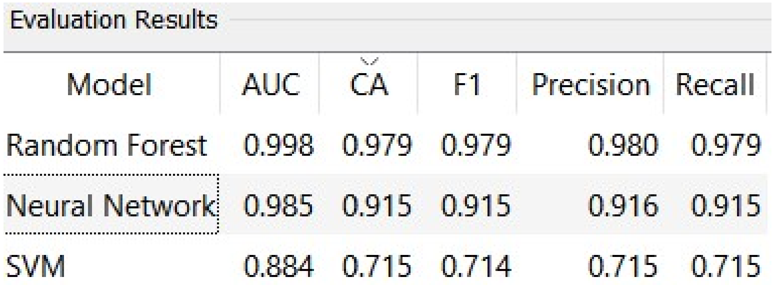
The model was made with two layers and compiled to return accuracy as the evaluation metric. After the model was trained and fitted, it was tested using KerasClassifier(build_fn=baseline_model, epochs=10, batch_size=5, verbose=0). The model was cross-validated using the k-fold method where the number of splits = 10. The baseline results yielded an accuracy of 65.20%.

The Random Forest model required discretization and binning of numeric and categorical variables in order to produce accurate classifications. This was completed using the cut() function from the Pandas package in Python. Some variables could be automatically binned using equal parts new1['Flights.Per.Year']=pd.cut(airline['Flights.Per.Year'], bins=10), while others had to be manually binned:

```
cut_l=['young adult','middle age','senior citizen']
cut_b=[15,29,55,85]
new1['Age']=pd.cut(new1['Age'],bins=cut_b,labels=cut_l)
```

The NumPy package was enlisted to help with dealing with large, multi-dimensional arrays and matrices. The prepared data frame was then split using the train_test_split() function where we made a 75/25 split before training and fitting the model. The Random Forest was created using RandomForestRegressor(n_estimators = 100, random_state = 42) with 100 decision trees. The predictions yielded an accuracy of 87.27%.

Interestingly enough, these results differed from the results taken from algorithms run in the Orange Workflow.



Evaluation Results

Model	AUC	CA	F1	Precision	Recall
Random Forest	0.998	0.979	0.979	0.980	0.979
Neural Network	0.985	0.915	0.915	0.916	0.915
SVM	0.884	0.715	0.714	0.715	0.715

Figure 12: Orange Workflow algorithm evaluation results

Because we can’t view the particular code or parameters that Orange is using backend, our team was not certain what the reason was for the discrepancy.

Business Recommendations Development Phase

Phase 6: Business Analysis

Once our team determined the attributes of the promoters, we began to develop the strategies that should be put in place to increase satisfaction by segment:

1. Since FlyFast airlines has the most number of passives and detractors for female passengers who are travelling for personal reasons, it would make sense to offer them special assistance in terms of food and service, improved in-flight entertainment services, and giving them seats with more leg room as they may be travelling with their children and comfort would be an important criteria for them.
2. There are the highest number of detractors when the flight is cancelled (or arrival delayed) by more than 100 minutes, so it may make sense to give them bonus miles or free access to the

airport lounges. Offering them accommodations if the flight is delayed by more than 600 minutes could help in reducing the detractors and passives. If they miss their connecting flight as a result of the delay, they should be given compensation or be scheduled in another flight.

3. People in the age group from 10-20 were predominantly detractors. This is due to them being bored and uncomfortable during the flight. More in-flight entertainment (cockpit tour) and a higher frequency of food and drinks would help convert this demographic to being promoters. Passengers older than 65 were also likely to be detractors. Although it is difficult for people this age to be comfortable, perhaps senior discounts, early/priority check-in, luggage assistance, and more drinks would help.
4. A common theme amongst detractors for the sentiment analysis was that food quality and dealing with luggage were two main issues. Another issue was having to pay to choose the seats that customers wanted. Providing better food and figuring out how to fix luggage problems would help FlyFast. Ending the policy of having to pay to choose seats would also help against losing customers that have a high price sensitivity.
5. Passengers who are highly price sensitive tend to be detractors and passives. People who fly frequently shouldn't be charged for choosing their seats of choice and giving more miles to them could help in retaining them, as they generate the most business for FlyFast. Sending promotional emails during the lean periods could help in attracting them.
6. Since FlyFast has the highest number of passives for the business travelers flying on the blue status airline, it would make sense to improve the in-flight entertainment services, and offer early/priority check-in, luggage assistance in terms of baggage allowance, better food/refreshments on flight and in the airport lounges to improve their experience.
7. FlyFast airlines has an enormous issue with providing excellent service to Economy and Economy Plus customers. Avoiding service polarity and lessening the experience gap between these customers and business class would be a great start to converting large numbers of detractors into promoters. Also offer a more luxurious experience overall to passengers who pay more. Platinum and Silver passengers should more often than not be promoters. They currently do not feel like their investment is paying off.

Phase 7: Develop Marketing Plan.

Finally, our team was ready to define the personas in each category, see what kind of customers were FlyFast's competitors' promoters and create marketing solutions to increase the NPS for each segment:

Sigma (Promoters)

- Name: Ms. Pamela Cooper
- Age: 32
- Gender: Female
- Location: New York
- Education: Bachelor of Arts
- Family members: 3
- Occupation: Arts faculty at NYU

Work role info: Pamela travels for leisure purposes mostly to visit art exhibitions. Comfort, price and Leisure are important factors; because of which she chooses Sigma.

Marketing message: In-flight entertainment, food and beverage quality and comfort are the things which have resulted in her being satisfied with her travel experience. Maybe signing up for a frequent flyer account can help in customer retention.

Cheapseats (Promoters)

- Name: Mr. Ron Bryant
- Age: 20
- Gender: Male
- Location: California
- Education: Engineering student at USC
- Family members: 2
- Occupation: Student

Work role info: Ron travels for leisure purposes and sometimes to attend seminars. Price and food are an important factor and because of this, he chooses to fly with Cheapseats.

Marketing message: Mostly young travelers prefer travelling with Cheapseats as price is a major factor for them. Digital and email marketing campaigns with promotions targeting the younger age groups can help to attract more of them. If the flight is not full then they should be considered for an upgrade. Improving in-flight entertainment services can act as an added advantage.

FlyFast (Promoter)

- Name: Mr. John Wick
- Age: 40 (35-55)
- Gender: Male
- Location: Texas
- Education: MBA
- Family members: 4
- Occupation: VP (marketing) at Schlumberger

Work role info: Being a high-ranking employee, John has to travel to various company locations to handle the various marketing campaigns. Time and comfort being important factors for him, he chooses to fly with FlyFast.

Marketing message: Since majority of the promoters are business travel passengers between the ages 35-55, FlyFast should look at the possibility of corporate tie-ups (B2B) which could act as a steady source of revenue. To woo more business passengers and improve on their customer retention (loyalty score), they should offer them bonus miles, improve their airport lounges, express check-in, offer extra baggage allowance, and if the flight gets delayed passengers should be compensated accordingly in addition to special food and beverage options. We believe these factors could make them choose FlyFast even for their leisure travel.

FlyFast (Detractors)

- Name: Mrs. Sue Brady
- Age: 65 (55-75)
- Gender: Female
- Location: Georgia
- Education: BS in Finance
- Family members: 6
- Occupation: Retired

Work role info: Sue travels quite often to Colorado to visit her children and grandchildren and chooses FlyFast because time and comfort are important factors for her.

Marketing message: Since most of the detractors are in the age group (55-75) and mostly female passengers, FlyFast should introduce special assistance services for the elderly travelers such as express check-in, baggage handling and wheelchair assistance, in-flight special care and assistance and better in-flight entertainment services. Another good option could be to upgrade the passenger to business class if the flight is not running full.

FlyFast (Passives)

- Name: Mr. Vincent Chase
- Age: 28
- Gender: Male
- Location: Illinois
- Education: MS in Supply Chain
- Family Members: 2
- Occupation: Supply Chain Analyst at FedEx

Work role info: Being a supply chain analyst, Vincent has to visit many of the company's warehouses. He ends up taking almost 60-70 flights per year, so time is an important factor for him.

Marketing message: Since a major chunk of the passengers between 20-40 are passives and are travelling for business purposes, FlyFast should consider compensating the travelers if the flight is delayed. They should be compensated and accommodated for a different flight as it is severely affecting their experience.