MODELING TECHNIQUES & VISUALIZATIONS

After conducting extensive visualizations, we were able to see which variables we would like to explore and predict more. We used four modeling techniques:

A. **Association Rule Mining:** A method to help us uncover relationships between seemingly unrelated data and find interesting relations and patterns between variables.
B. **Linear Modeling:** Used to help us find relationships between sets of data where we were able generate prediction models created from a statistical analysis process. These models represented the correlation between certain variables.
C. **Support Vector Modeling (SVM):** A supervised learning technique to train an algorithm on the survey data set to which we supervise and create predictions by testing what variables can affect the NPS score.
D. **Text mining:** A method that looks for unexpected patterns in the survey data set and focus on the approach and strategy to identify word frequencies

Association Rule Mining

We did not input gender as a column in association rule as it can be used as a machine learning model. To avoid bias and adhere to the rules we did not use Gender as input in our model.

Detractor groups with minimum support of 0.005, and confidence of 0.5(top results)

LHS	RHS	support	confidence	coverage	lift	count
All	All	All	All	All	All	4372 ... 1
{a_survey.Age=60-85 Age}	{a_survey.Likelihood.to.recommend=Detractors}	0.120	0.513	0.233	1.744	10,313.000
{a_survey.Age=60-85 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Detractors}	0.115	0.506	0.227	1.722	9,909.000
{a_survey.Age=60-85 Age,a_survey.Airline.Status=Blue}	{a_survey.Likelihood.to.recommend=Detractors}	0.102	0.592	0.172	2.013	8,792.000
{a_survey.Age=60-85 Age,a_survey.Airline.Status=Blue,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Detractors}	0.098	0.585	0.167	1.992	8,438.000
{a_survey.Class=Eco,a_survey.Age=60-85 Age}	{a_survey.Likelihood.to.recommend=Detractors}	0.096	0.517	0.186	1.760	8,303.000
{a_survey.Class=Eco,a_survey.Age=60-85 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Detractors}	0.093	0.511	0.181	1.739	7,988.000
{a_survey.Class=Eco,a_survey.Age=60-85 Age,a_survey.Airline.Status=Blue}	{a_survey.Likelihood.to.recommend=Detractors}	0.082	0.598	0.137	2.035	7,094.000
{a_survey.Class=Eco,a_survey.Age=60-85 Age,a_survey.Airline.Status=Blue,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Detractors}	0.079	0.592	0.133	2.015	6,817.000
{a_survey.Shopping.Amount.at.Airport=No Shopping,a_survey.Age=60-85 Age}	{a_survey.Likelihood.to.recommend=Detractors}	0.075	0.526	0.143	1.790	6,500.000
{a_survey.Shopping.Amount.at.Airport=No Shopping,a_survey.Age=60-85 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Detractors}	0.072	0.518	0.139	1.764	6,225.000

LHS	RHS	support	confidence	coverage	lift	count
All	All	All	All	All	All	4372
{a_survey.Price.Sensitivity=1,a_survey.Age=60-85 Age,a_survey.Airline.Status=Blue}	{a_survey.Likelihood.to.recommend=Detractors}	0.067	0.574	0.116	1.954	5,771.000
{a_survey.Shopping.Amount.at.Airport=No Shopping,a_survey.Age=60-85 Age,a_survey.Airline.Status=Blue}	{a_survey.Likelihood.to.recommend=Detractors}	0.065	0.601	0.108	2.044	5,613.000
{a_survey.Price.Sensitivity=1,a_survey.Age=60-85 Age,a_survey.Airline.Status=Blue,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Detractors}	0.065	0.570	0.113	1.938	5,567.000
{a_survey.Shopping.Amount.at.Airport=No Shopping,a_survey.Age=60-85 Age,a_survey.Airline.Status=Blue,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Detractors}	0.062	0.593	0.105	2.019	5,371.000
{a_survey.Class=Eco,a_survey.Shopping.Amount.at.Airport=No Shopping,a_survey.Age=60-85 Age}	{a_survey.Likelihood.to.recommend=Detractors}	0.061	0.527	0.115	1.794	5,233.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Age=60-85 Age,a_survey.Airline.Status=Blue}	{a_survey.Likelihood.to.recommend=Detractors}	0.059	0.519	0.113	1.767	5,083.000
{a_survey.Class=Eco,a_survey.Shopping.Amount.at.Airport=No Shopping,a_survey.Age=60-85 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Detractors}	0.058	0.520	0.112	1.768	5,013.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Age=60-85 Age,a_survey.Airline.Status=Blue,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Detractors}	0.056	0.511	0.110	1.739	4,849.000
{a_survey.Class=Eco,a_survey.Price.Sensitivity=1,a_survey.Age=60-85 Age,a_survey.Airline.Status=Blue}	{a_survey.Likelihood.to.recommend=Detractors}	0.053	0.582	0.092	1.980	4,608.000
{a_survey.Class=Eco,a_survey.Shopping.Amount.at.Airport=No Shopping,a_survey.Age=60-85 Age,a_survey.Airline.Status=Blue}	{a_survey.Likelihood.to.recommend=Detractors}	0.053	0.602	0.087	2.049	4,537.000

Promotor groups- with minimum support of 0.005, and confidence of 0.5(top results)

LHS	RHS	support	confidence	coverage	lift	count
All	All	All	All	All	All	All
{a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Promoters}	0.261	0.518	0.505	1.336	22,550.000
{a_survey.Class=Eco,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Promoters}	0.213	0.512	0.416	1.321	18,383.000
{a_survey.Price.Sensitivity=1,a_survey.Age=33-59 Age}	{a_survey.Likelihood.to.recommend=Promoters}	0.200	0.527	0.379	1.360	17,228.000
{a_survey.Price.Sensitivity=1,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Promoters}	0.198	0.546	0.362	1.408	17,057.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Age=33-59 Age}	{a_survey.Likelihood.to.recommend=Promoters}	0.180	0.514	0.350	1.328	15,548.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Promoters}	0.178	0.536	0.333	1.384	15,391.000
{a_survey.Class=Eco,a_survey.Price.Sensitivity=1,a_survey.Age=33-59 Age}	{a_survey.Likelihood.to.recommend=Promoters}	0.162	0.524	0.310	1.351	14,014.000
{a_survey.Class=Eco,a_survey.Price.Sensitivity=1,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Promoters}	0.161	0.541	0.297	1.396	13,870.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Class=Eco,a_survey.Age=33-59 Age}	{a_survey.Likelihood.to.recommend=Promoters}	0.147	0.510	0.289	1.316	12,705.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Class=Eco,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Promoters}	0.146	0.530	0.275	1.368	12,571.000

LHS	RHS	support	confidence	coverage	lift	count
All	All	All	All	All	All	All
{a_survey.Shopping.Amount.at.Airport=No Shopping,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Promoters}	0.139	0.505	0.275	1.303	11,968.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Price.Sensitivity=1,a_survey.Age=33-59 Age}	{a_survey.Likelihood.to.recommend=Promoters}	0.136	0.544	0.251	1.403	11,766.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Price.Sensitivity=1,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Promoters}	0.135	0.564	0.240	1.455	11,665.000
{a_survey.Shopping.Amount.at.Airport=Shopped,a_survey.Age=33-59 Age}	{a_survey.Likelihood.to.recommend=Promoters}	0.124	0.515	0.241	1.328	10,680.000
{a_survey.Shopping.Amount.at.Airport=Shopped,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Promoters}	0.123	0.533	0.230	1.376	10,582.000
{a_survey.Airline.Status=Silver}	{a_survey.Likelihood.to.recommend=Promoters}	0.120	0.595	0.201	1.537	10,311.000
{a_survey.Airline.Status=Silver,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Promoters}	0.118	0.612	0.193	1.579	10,196.000
{a_survey.Class=Eco,a_survey.Shopping.Amount.at.Airport=No Shopping,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Promoters}	0.114	0.500	0.228	1.292	9,855.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Class=Eco,a_survey.Price.Sensitivity=1,a_survey.Age=33-59 Age}	{a_survey.Likelihood.to.recommend=Promoters}	0.111	0.540	0.206	1.395	9,582.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Class=Eco,a_survey.Price.Sensitivity=1,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Promoters}	0.110	0.559	0.197	1.443	9,496.000

Passives

LHS	RHS	support	confidence	coverage	lift	count
All	All	All	All	All	All	All
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Price.Sensitivity=1,a_survey.Eating.and.Drinking.at.Airport=Didnt eat at airport}	{a_survey.Likelihood.to.recommend=Passives}	0.009	0.509	0.018	1.596	798.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Didnt eat at airport}	{a_survey.Likelihood.to.recommend=Passives}	0.009	0.511	0.018	1.603	773.000
{a_survey.Price.Sensitivity=1,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Didnt eat at airport}	{a_survey.Likelihood.to.recommend=Passives}	0.008	0.507	0.017	1.592	725.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Class=Eco,a_survey.Price.Sensitivity=1,a_survey.Eating.and.Drinking.at.Airport=Didnt eat at airport}	{a_survey.Likelihood.to.recommend=Passives}	0.007	0.502	0.014	1.574	622.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Class=Eco,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Didnt eat at airport}	{a_survey.Likelihood.to.recommend=Passives}	0.007	0.504	0.014	1.582	611.000
{a_survey.Departure.Delay.in.Minutes=> 5 mins delay in Depart,a_survey.Age=60-85 Age,a_survey.Airline.Status=Silver}	{a_survey.Likelihood.to.recommend=Passives}	0.007	0.581	0.012	1.824	593.000
{a_survey.Departure.Delay.in.Minutes=> 5 mins delay in Depart,a_survey.Age=60-85 Age,a_survey.Airline.Status=Silver,a_survey.Eating.and.Drinking.at.Airport=Eat at Airport}	{a_survey.Likelihood.to.recommend=Passives}	0.007	0.585	0.012	1.837	583.000
{a_survey.Class=Eco,a_survey.Price.Sensitivity=1,a_survey.Age=33-59 Age,a_survey.Eating.and.Drinking.at.Airport=Didnt eat at airport}	{a_survey.Likelihood.to.recommend=Passives}	0.007	0.502	0.013	1.574	562.000
{a_survey.Departure.Delay.in.Minutes=No or < 5 mins delay in depart,a_survey.Shopping.Amount.at.Airport=Shopped,a_survey.Eating.and.Drinking.at.Airport=Didnt eat at airport}	{a_survey.Likelihood.to.recommend=Passives}	0.006	0.510	0.012	1.599	536.000
{a_survey.Price.Sensitivity=1,a_survey.Shopping.Amount.at.Airport=Shopped,a_survey.Eating.and.Drinking.at.Airport=Didnt eat at airport}	{a_survey.Likelihood.to.recommend=Passives}	0.006	0.516	0.012	1.618	513.000

Linear Modeling

Except for model with year of first flight as indicator for likelihood to recommend, the standard error for all these linear models are less than 0.05, so we can reject the null hypothesis and say that the R squared values are statistically significant i.e the results were probably not due to randomness.

```
Call:
lm(formula = Likelihood.to.recommend ~ Age, data = survey)

Residuals:
    Min      1Q  Median      3Q     Max
-7.1681 -1.3790  0.4834  1.6577  3.7586

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  8.580949   0.021114  406.41   <2e-16 ***
Age         -0.027525   0.000428  -64.31   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.193 on 88094 degrees of freedom
Multiple R-squared:  0.04485,	Adjusted R-squared:  0.04484
F-statistic:  4136 on 1 and 88094 DF,  p-value: < 2.2e-16
```

Age accounts for about 4% of the variability in likelihood to recommend, to know more we divided the age into groups to understand which age groups were giving more and less likelihood to recommend score

```
Call:
lm(formula = Likelihood.to.recommend ~ Airline.Status, data = survey)

Residuals:
    Min      1Q  Median      3Q     Max 
-6.9716 -1.5851  0.4149  1.4149  3.1537 

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)    
(Intercept)            6.846268   0.008674  789.32   <2e-16 ***
Airline.StatusGold     1.125365   0.026201   42.95   <2e-16 ***
Airline.StatusPlatinum 0.615245   0.040206   15.30   <2e-16 ***
Airline.StatusSilver   1.738841   0.018228   95.40   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.127 on 88092 degrees of freedom
Multiple R-squared:  0.1012,	Adjusted R-squared:  0.1011 
F-statistic:  3305 on 3 and 88092 DF,  p-value: < 2.2e-16
```

Airline status accounts for about 10% of the variability in likelihood to recommend

```
Call:
lm(formula = Likelihood.to.recommend ~ Price.Sensitivity, data = survey)

Residuals:
   Min     1Q Median     3Q    Max 
-6.784 -1.412  0.588  1.588  3.705 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)        7.78430    0.01917  406.05   <2e-16 ***
Price.Sensitivity -0.37230    0.01381  -26.97   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.235 on 88094 degrees of freedom
Multiple R-squared:  0.008187,	Adjusted R-squared:  0.008175 
F-statistic: 727.2 on 1 and 88094 DF,  p-value: < 2.2e-16
```

Price sensitivity accounts for about 1% of the variability in likelihood to recommend

```
Call:
lm(formula = Likelihood.to.recommend ~ Year.of.First.Flight,
    data = survey)

Residuals:
   Min     1Q Median     3Q    Max
-6.309 -1.309  0.691  1.691  2.691

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          7.211e+00  5.093e+00   1.416    0.157
Year.of.First.Flight 4.858e-05  2.538e-03   0.019    0.985

Residual standard error: 2.244 on 88094 degrees of freedom
Multiple R-squared:  4.161e-09, Adjusted R-squared:  -1.135e-05
F-statistic: 0.0003665 on 1 and 88094 DF,  p-value: 0.9847
```

First year flyers do not have a linear relation to likelihood to recommend.

```
Call:
lm(formula = Likelihood.to.recommend ~ Loyalty, data = survey)

Residuals:
    Min      1Q  Median      3Q     Max
-7.1868 -1.1916  0.5453  1.8111  3.1718

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 7.497789   0.008375  895.30   <2e-16 ***
Loyalty     0.689012   0.013905   49.55   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.213 on 88094 degrees of freedom
Multiple R-squared:  0.02712,   Adjusted R-squared:  0.02711
F-statistic:  2455 on 1 and 88094 DF,  p-value: < 2.2e-16
```

Loyalty accounts for about 2% of the variability in likelihood to recommend

```
Call:
lm(formula = Likelihood.to.recommend ~ Shopping.Amount.at.Airport,
    data = survey)

Residuals:
    Min      1Q  Median      3Q     Max
-6.6345 -1.2753  0.7058  1.7247  2.7247

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)                7.2753161  0.0084415 861.848   <2e-16 ***
Shopping.Amount.at.Airport 0.0012602  0.0001414   8.915   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.243 on 88094 degrees of freedom
Multiple R-squared:  0.0009014, Adjusted R-squared:  0.0008901
F-statistic: 79.48 on 1 and 88094 DF,  p-value: < 2.2e-16
```

Shopping has no linear relation to likelihood to recommend.

```
Call:
lm(formula = Likelihood.to.recommend ~ Type.of.Travel, data = survey)

Residuals:
    Min      1Q  Median      3Q     Max
-7.1720 -1.1720  0.5378  1.5378  4.5378

Coefficients:
                              Estimate Std. Error t value Pr(>|t|)
(Intercept)                   8.172019   0.008063 1013.46   <2e-16 ***
Type.of.TravelMileage tickets -0.362896   0.023773  -15.27   <2e-16 ***
Type.of.TravelPersonal Travel -2.709775   0.013942 -194.36   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.873 on 88093 degrees of freedom
Multiple R-squared:  0.3031,    Adjusted R-squared:  0.3031
F-statistic: 1.916e+04 on 2 and 88093 DF,  p-value: < 2.2e-16
```

Type of travel accounts for about 30% of the variability in likelihood to recommend

```
Call:
lm(formula = Likelihood.to.recommend ~ Eating.and.Drinking.at.Airport,
    data = survey)

Residuals:
    Min      1Q  Median      3Q     Max
-7.8302 -1.1864  0.6202  1.7652  2.9103

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)
(Intercept)                    7.0897171  0.0123895  572.24   <2e-16 ***
Eating.and.Drinking.at.Airport 0.0032231  0.0001446   22.29   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.237 on 88094 degrees of freedom
Multiple R-squared:  0.005608,  Adjusted R-squared:  0.005597
F-statistic: 496.8 on 1 and 88094 DF,  p-value: < 2.2e-16
```

Eating and Drinking has a negligible linear relationship with likelihood to recommend.

```
Call:
lm(formula = Likelihood.to.recommend ~ Total.Freq.Flyer.Accts,
    data = survey)

Residuals:
   Min     1Q Median     3Q    Max
-7.150 -1.327  0.673  1.838  2.838

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)            7.162390   0.009526  751.91   <2e-16 ***
Total.Freq.Flyer.Accts 0.164607   0.006552   25.12   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.236 on 88094 degrees of freedom
Multiple R-squared:  0.007113,  Adjusted R-squared:  0.007102
F-statistic: 631.1 on 1 and 88094 DF,  p-value: < 2.2e-16
```

The total frequent flyer accounts have a negligible linear relationship with likelihood to recommend.

```
Call:
lm(formula = Likelihood.to.recommend ~ Flights.Per.Year, data = survey)

Residuals:
    Min      1Q  Median      3Q     Max 
-7.0550 -1.3105  0.4662  1.6523  5.5188 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)       8.055034   0.012652  636.65   <2e-16 ***
Flights.Per.Year -0.037228   0.000514  -72.42   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.18 on 88094 degrees of freedom
Multiple R-squared:  0.0562,	Adjusted R-squared:  0.05619 
F-statistic:  5245 on 1 and 88094 DF,  p-value: < 2.2e-16
```

Flights per year have a negligible linear relationship with likelihood to recommend.

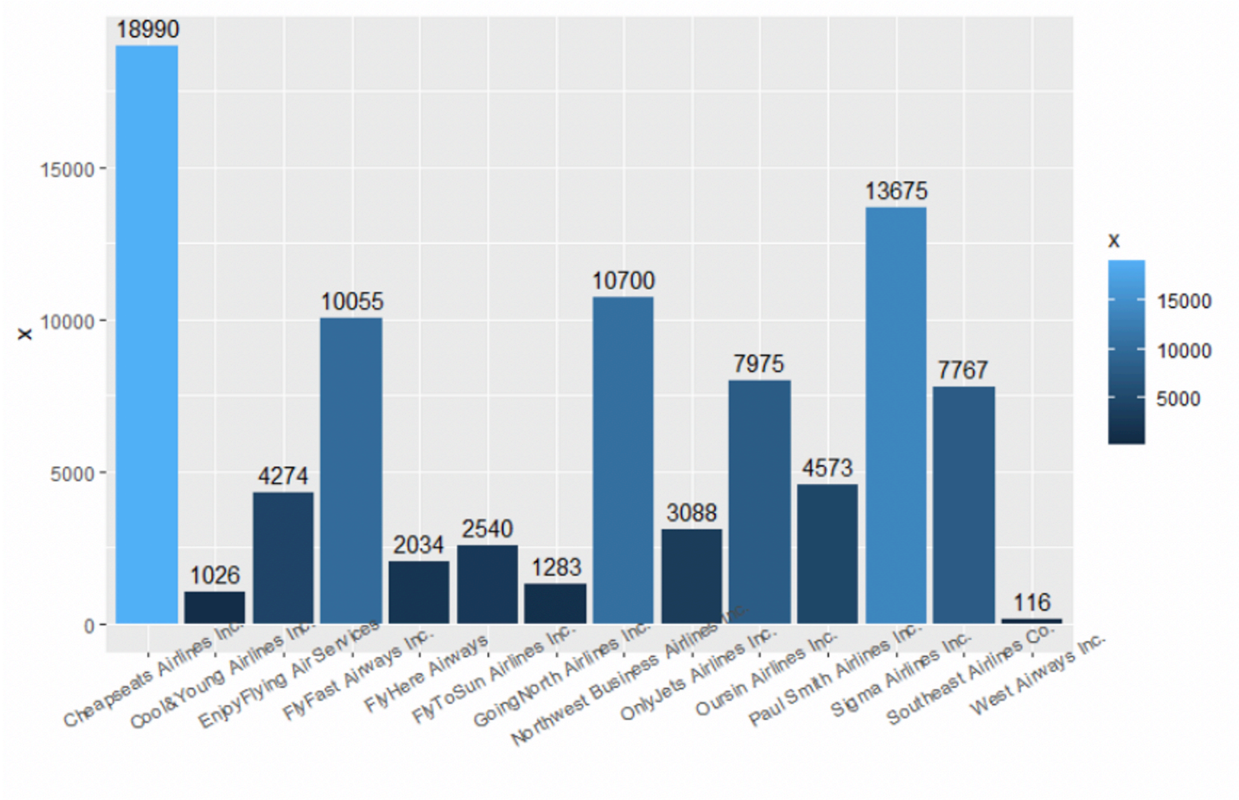
```
Call:
lm(formula = Likelihood.to.recommend ~ Airline.Status + Gender + 
    Type.of.Travel, data = survey)

Residuals:
    Min      1Q  Median      3Q     Max 
-7.6043 -1.1499  0.2689  1.3163  4.8501 

Coefficients:
                             Estimate Std. Error  t value Pr(>|t|)    
(Intercept)                   7.68367    0.01083  709.427  < 2e-16 ***
Airline.StatusGold            0.76972    0.02207   34.881  < 2e-16 ***
Airline.StatusPlatinum        0.16281    0.03385    4.810 1.51e-06 ***
Airline.StatusSilver          1.43031    0.01538   92.974  < 2e-16 ***
GenderMale                    0.15093    0.01224   12.332  < 2e-16 ***
Type.of.TravelMileage tickets -0.20621    0.02271   -9.079  < 2e-16 ***
Type.of.TravelPersonal Travel -2.53377    0.01352 -187.409  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.782 on 88089 degrees of freedom
Multiple R-squared:  0.369,	Adjusted R-squared:  0.369 
F-statistic:  8587 on 6 and 88089 DF,  p-value: < 2.2e-16
```

Flights per year accounts for about 5% of the variability in likelihood to recommend.



Airline status, Gender and type of travel accounts for about 36% of the variability in likelihood to recommend

All numeric data except binomial data

```
Call:
lm(formula = Likelihood.to.recommend ~ Arrival.Delay.in.Minutes +
    Departure.Delay.in.Minutes + Age + Price.Sensitivity + Flights.Per.Year +
    Loyalty + Total.Freq.Flyer.Accts + Shopping.Amount.at.Airport +
    Eating.and.Drinking.at.Airport + Flight.time.in.minutes +
    Flight.Distance, data = survey.p)

Residuals:
    Min      1Q  Median      3Q     Max
-8.3291 -1.3076  0.4625  1.6088  6.9618

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)
(Intercept)                    9.563e+00  3.717e-02 257.272  < 2e-16 ***
Arrival.Delay.in.Minutes      -8.863e-03  7.462e-04 -11.877  < 2e-16 ***
Departure.Delay.in.Minutes     3.492e-03  7.556e-04   4.622 3.81e-06 ***
Age                           -2.602e-02  4.806e-04 -54.145  < 2e-16 ***
Price.Sensitivity             -4.054e-01  1.337e-02 -30.326  < 2e-16 ***
Flights.Per.Year              -3.302e-02  7.307e-04 -45.194  < 2e-16 ***
Loyalty                       -1.406e-01  2.022e-02  -6.956 3.54e-12 ***
Total.Freq.Flyer.Accts        -6.811e-02  7.365e-03  -9.248  < 2e-16 ***
Shopping.Amount.at.Airport     3.516e-04  1.356e-04   2.592  0.00954 **
Eating.and.Drinking.at.Airport 3.089e-03  1.410e-04  21.909  < 2e-16 ***
Flight.time.in.minutes        -1.450e-03  4.879e-04  -2.972  0.00296 **
Flight.Distance                2.303e-04  5.904e-05   3.900 9.62e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.121 on 86246 degrees of freedom
  (1842 observations deleted due to missingness)
Multiple R-squared:  0.1083,    Adjusted R-squared:  0.1082
F-statistic: 952.6 on 11 and 86246 DF,  p-value: < 2.2e-16
```

R-squared: 0.1083, p-value: statistically significant at 0.05 level.
Although R-squared is not high enough, this model can be trusted because it is the analysis of human behaviors. "In the analysis of human behavior, which is notoriously unpredictable, an R-squared of .20 or .30 could be considered extremely good." So, this result can be considered good. We use this model not just to predict but to observe which parameter is positive and which one is negative. From the summary, the increase of Departure.Delay.in.Minutes, Shopping.Amount.at.Airport, Eating.and.Drinking.at.Airport, Flight.Distance can improve likelihood.to.recommend scores and the increase of Arrival.Delay.in.Minutes, Age, Price.Sensitivity, Flights.Per.Year, Loyalty, Total.Freq.Flyer.Accts, Flight.time.in.minutes may decrease likelihood.to.recommend scores.

Flight Data

```
Call:
lm(formula = Likelihood.to.recommend ~ Arrival.Delay.in.Minutes +
    Departure.Delay.in.Minutes + Flight.time.in.minutes + Flight.Distance,
    data = survey.p)

Residuals:
    Min      1Q  Median      3Q     Max
-6.6242 -1.3817  0.6014  1.6259  6.6307

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)                7.381e+00  1.581e-02 466.951  < 2e-16 ***
Arrival.Delay.in.Minutes  -8.583e-03  7.861e-04 -10.919  < 2e-16 ***
Departure.Delay.in.Minutes  3.103e-03  7.961e-04   3.898 9.69e-05 ***
Flight.time.in.minutes    -1.379e-03  5.141e-04  -2.682  0.00732 **
Flight.Distance            2.206e-04  6.221e-05   3.547  0.00039 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.234 on 86253 degrees of freedom
  (1842 observations deleted due to missingness)
Multiple R-squared:  0.01007,   Adjusted R-squared:  0.01002
F-statistic: 219.3 on 4 and 86253 DF,  p-value: < 2.2e-16
```

Because its R-squared is just 0.01 and it means that likelihood.to.recommend is accounted for by 1% of this model. Obviously, this model is not a good model and for the purpose to avoid bias, we don't use it to do analysis.

Client Data

```
Call:
lm(formula = Likelihood.to.recommend ~ Age + Gender + Price.Sensitivity +
    Flights.Per.Year + Loyalty + Total.Freq.Flyer.Accts + Shopping.Amount.at.Airport +
    Eating.and.Drinking.at.Airport, data = survey.p)

Residuals:
   Min     1Q Median     3Q    Max 
-8.531 -1.301  0.489  1.610  4.858 

Coefficients:
                                 Estimate Std. Error t value Pr(>|t|)    
(Intercept)                     9.2229630  0.0353928 260.589  < 2e-16 ***
Age                            -0.0244803  0.0004759 -51.439  < 2e-16 ***
GenderMale                      0.4631236  0.0146082  31.703  < 2e-16 ***
Price.Sensitivity              -0.3903164  0.0132252 -29.513  < 2e-16 ***
Flights.Per.Year               -0.0336873  0.0007222 -46.644  < 2e-16 ***
Loyalty                        -0.1144376  0.0200226  -5.715 1.10e-08 ***
Total.Freq.Flyer.Accts         -0.0621453  0.0072893  -8.526  < 2e-16 ***
Shopping.Amount.at.Airport      0.0007854  0.0001350   5.819 5.96e-09 ***
Eating.and.Drinking.at.Airport  0.0028281  0.0001398  20.235  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.119 on 88087 degrees of freedom
  (4 observations deleted due to missingness)
Multiple R-squared:  0.108,	Adjusted R-squared:  0.108 
F-statistic:  1334 on 8 and 88087 DF,  p-value: < 2.2e-16
```

The R-squared is 0.108 and it is statistically significant at 0.05 level. However, it is not as detailed as our first model including all fight and client numeric data. Therefore, to avoid bias (just rely on client data), we do not use this model to do analysis.

Test

```
predDF<- data.frame(Arrival.Delay.in.Minutes=15.38,Departure.Delay.in.Minutes=14.96,Age=46.17,Gender=0.5634,Price.Sensitivity=1.2
                    Flights.Per.Year=20,Loyalty=-0.27294,Total.Freq.Flyer.Accts=0.8915,Shopping.Amount.at.Airport=26.69,
                    Eating.and.Drinking.at.Airport=67.98,Flight.time.in.minutes=113.1,Flight.Distance=809.9)
predict(model.all,predDF)#Mean.Likelihood.to.recommend=7.318498, result = 7.318364
mean(survey.p$Likelihood.to.recommend)
```

We use the mean value in airData dataset to test our model. The prediction is 7.318364 and the mean value in the dataset is 7.318498.

Also, we tried our first model with different types of dataset such as Type.of.Travel, Gender, Airline.Status and etc. For example (below):

```
Call:
lm(formula = Likelihood.to.recommend ~ Arrival.Delay.in.Minutes +
    Departure.Delay.in.Minutes + Age + Price.Sensitivity + Flights.Per.Year +
    Loyalty + Total.Freq.Flyer.Accts + Shopping.Amount.at.Airport +
    Eating.and.Drinking.at.Airport + Flight.time.in.minutes +
    Flight.Distance, data = Flight.Business)

Residuals:
   Min     1Q Median     3Q    Max
-7.777 -1.154  0.529  1.536  4.056

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)
(Intercept)                    9.885e+00  1.245e-01  79.390  < 2e-16 ***
Arrival.Delay.in.Minutes      -9.790e-04  2.633e-03  -0.372  0.71004
Departure.Delay.in.Minutes    -3.687e-03  2.603e-03  -1.416  0.15677
Age                           -2.448e-02  1.638e-03 -14.948  < 2e-16 ***
Price.Sensitivity             -4.434e-01  4.592e-02  -9.656  < 2e-16 ***
Flights.Per.Year              -3.875e-02  2.508e-03 -15.446  < 2e-16 ***
Loyalty                       -1.814e-01  6.685e-02  -2.713  0.00668 **
Total.Freq.Flyer.Accts        -4.380e-02  2.396e-02  -1.828  0.06754 .
Shopping.Amount.at.Airport     5.674e-04  4.507e-04   1.259  0.20807
Eating.and.Drinking.at.Airport 3.023e-03  4.611e-04   6.557 5.87e-11 ***
Flight.time.in.minutes         1.460e-04  1.628e-03   0.090  0.92854
Flight.Distance                3.125e-05  1.991e-04   0.157  0.87529
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.039 on 7124 degrees of freedom
  (61 observations deleted due to missingness)
Multiple R-squared:  0.1179,	Adjusted R-squared:  0.1165
F-statistic: 86.54 on 11 and 7124 DF,  p-value: < 2.2e-16
```

Class: Business

```
Call:
lm(formula = Likelihood.to.recommend ~ Arrival.Delay.in.Minutes +
    Departure.Delay.in.Minutes + Age + Price.Sensitivity + Flights.Per.Year +
    Loyalty + Total.Freq.Flyer.Accts + Shopping.Amount.at.Airport +
    Eating.and.Drinking.at.Airport + Flight.time.in.minutes +
    Flight.Distance, data = customer.PT)

Residuals:
    Min      1Q  Median      3Q     Max
-8.7233 -0.9251  0.5547  1.1649  4.0202

Coefficients:
                                Estimate Std. Error t value Pr(>|t|)
(Intercept)                    8.483e+00  4.117e-02 206.064  < 2e-16 ***
Arrival.Delay.in.Minutes      -6.308e-03  7.831e-04  -8.055 8.14e-16 ***
Departure.Delay.in.Minutes     2.886e-03  7.931e-04   3.639 0.000274 ***
Age                           -6.067e-03  6.034e-04 -10.053  < 2e-16 ***
Price.Sensitivity             -1.335e-01  1.459e-02  -9.148  < 2e-16 ***
Flights.Per.Year              -8.303e-03  8.529e-04  -9.735  < 2e-16 ***
Loyalty                       -4.192e-02  2.043e-02  -2.051 0.040233 *
Total.Freq.Flyer.Accts        -6.995e-03  7.298e-03  -0.959 0.337785
Shopping.Amount.at.Airport     9.405e-04  1.398e-04   6.730 1.72e-11 ***
Eating.and.Drinking.at.Airport 3.942e-03  1.459e-04  27.016  < 2e-16 ***
Flight.time.in.minutes        -1.166e-03  5.090e-04  -2.290 0.021998 *
Flight.Distance                1.904e-04  6.168e-05   3.088 0.002018 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.731 on 53136 degrees of freedom
  (815 observations deleted due to missingness)
Multiple R-squared:  0.02856,	Adjusted R-squared:  0.02836
F-statistic:   142 on 11 and 53136 DF,  p-value: < 2.2e-16
```

Type of travel: Personal travel

```
Call:
lm(formula = Likelihood.to.recommend ~ Arrival.Delay.in.Minutes +
    Departure.Delay.in.Minutes + Age + Price.Sensitivity + Flights.Per.Year +
    Loyalty + Total.Freq.Flyer.Accts + Shopping.Amount.at.Airport +
    Eating.and.Drinking.at.Airport + Flight.time.in.minutes +
    Flight.Distance, data = customer.Blue)

Residuals:
    Min      1Q  Median      3Q     Max
-7.6500 -1.5263  0.4003  1.6904  8.8405

Coefficients:
                                 Estimate Std. Error t value Pr(>|t|)
(Intercept)                     9.239e+00  4.499e-02 205.359  < 2e-16 ***
Arrival.Delay.in.Minutes       -1.055e-02  9.145e-04 -11.541  < 2e-16 ***
Departure.Delay.in.Minutes      3.447e-03  9.249e-04   3.727 0.000194 ***
Age                            -2.680e-02  5.662e-04 -47.341  < 2e-16 ***
Price.Sensitivity              -3.851e-01  1.580e-02 -24.376  < 2e-16 ***
Flights.Per.Year               -3.325e-02  8.649e-04 -38.445  < 2e-16 ***
Loyalty                        -2.067e-01  2.524e-02  -8.189 2.69e-16 ***
Total.Freq.Flyer.Accts         -9.467e-02  9.058e-03 -10.451  < 2e-16 ***
Shopping.Amount.at.Airport     -2.709e-05  1.673e-04  -0.162 0.871391
Eating.and.Drinking.at.Airport  2.675e-03  1.789e-04  14.953  < 2e-16 ***
Flight.time.in.minutes         -1.644e-03  5.982e-04  -2.749 0.005979 **
Flight.Distance                 2.537e-04  7.243e-05   3.502 0.000461 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.157 on 58781 degrees of freedom
  (1359 observations deleted due to missingness)
Multiple R-squared:  0.1126,    Adjusted R-squared:  0.1124
F-statistic: 677.9 on 11 and 58781 DF,  p-value: < 2.2e-16
```

Airline.Status: Blue

Linear Function:

```
#Model function
lmf<- function(b){
  model.aa<- lm(formula=Likelihood.to.recommend~Arrival.Delay.in.Minutes+Departure.Delay.in.Minutes+Age
               +Price.Sensitivity+Flights.Per.Year+Loyalty+Total.Freq.Flyer.Accts
               + Shopping.Amount.at.Airport+ Eating.and.Drinking.at.Airport+Flight.time.in.minutes
               +Flight.Distance, data= b)
  return(model.aa)
}
```

It is the same as what we do to simplify the NPS calculation process.

Support Vector Modeling

When creating our SVM Model, we also created a new data frame with certain variables we want to predict; the variables we thought might have affect a customer's recommendation score. Among these variables were age, ticket prices, flight delay in both arrival and departure, types of travel, class, and cancelled flights.

```
Support Vector Machine object of class "ksvm"

SV type: C-svc  (classification)
 parameter : cost C = 5

Gaussian Radial Basis kernel function.
 Hyperparameter : sigma =  0.142332781770154

Number of Support Vectors : 5442

Objective Function Value : -24684.14
Training error : 1
Cross validation error : 0.08183
Probability model included.
```

While getting a relatively good cross validation error (~8%) to create our predictions, our prediction models were not as effective as we thought. As a team, we collectively decided not to rely on our SVM models to predict which variables can account for recommendation score. We decided to use Text Mining as an alternative.

Text Mining

Finding out if the feedback was negative or positive

Negative words in the feedback (Freetext)

- **Delay** was mentioned 80 times in total
- 178 negative words matched

```
matchedNwords
      delayed         worst          poor            bad         delay       terrible        delays
           49            30            29             20            20             16            12
      cramped       problem          lack         missed          miss           lost uncomfortable
           12            10             9              9             9              8             8
   uneventful          rude        issues  disappointing      problems      appalling      horrible
            8             7             7              7             6              6             6
    expensive         issue         worse          fault     emergency   disappointed        frozen
            5             4             4              4             4              3             3
  frustrating    ridiculous         sucks           cold          hard     disgusting        bother
            3             3             3              3             3              3             3
        awful    unpleasant        boring        limited          mess         stress      mediocre
            3             3             3              2             2              2             2
        chaos        poorly        broken          wrong     nightmare         bumped       garbage
            2             2             2              2             2              2             2
   complaints    unreliable         death          cheap   bereavement      bothering          slow
            2             2             2              2             2              2             2
     disaster          lose       hostile         losing       torture       annoying unfortunately
            2             2             2              2             2              2             2
        funny     stressful        brutal      complaint         noise        crowded         cramp
            2             2             2              2             2              2             1
       grumpy       cracked      careless      defective       chaotic        decline       unhappy
            1             1             1              1             1              1             1
  unfortunate       blatant      confused      disagreed     disregard      allergies       allergy
            1             1             1              1             1              1             1
 disingenuous       trouble    aggressive     inadequate         crack         ripped         dirty
            1             1             1              1             1              1             1
        blame      isolated         upset          froze    irritating          lying inconvenience
            1             1             1              1             1              1             1
    struggled        insane         break         crappy  unacceptable        refused       sub-par
            1             1             1              1             1              1             1
         fuss        danger    impossible            lie     notorious        smelled     apathetic
            1             1             1              1             1              1             1
     disgrace          worn      disabled           loud         worry          bored        lacked
            1             1             1              1             1              1             1
         suck         lacks      marginal        stooges       shocked        naively         shame
            1             1             1              1             1              1             1
     terribly    concession         stuck           joke   disappoints          steep      delaying
            1             1             1              1             1              1             1

     panicked        limits      criminal           bump      distress         savage         fails
            1             1             1              1             1              1             1
   bothersome       friggin         stiff         failed  disorganized    distressing       ashamed
            1             1             1              1             1              1             1
      mocking        unable        wasted         ruined   complicated         cringe       contend
            1             1             1              1             1              1             1
     refusing     negatives     immovable            cry      negative      vibration      complain
            1             1             1              1             1              1             1
      trapped     difficult     confusing         slower    difficulty         afraid           pry
            1             1             1              1             1              1             1
        bland      damaging      strictly disappointments     hassled          tired      uncaring
            1             1             1              1             1              1             1
      mistake       lacking        damage
            1             1             1
```

Positive words in the feedback (Freetext)

- 164 positive words matched

```
matchedPWords
        good           great     comfortable        friendly            nice            best            like
          70              40              37              28              24              21              20
        well          better       excellent         helpful        pleasant          enough            free
          19              19              15              14              12              12              11
   recommend       efficient          pretty          smooth       attentive            work          decent
          10               9               8               8               8               8               7
        easy       available       courteous          polite           worth        adequate           smile
           7               7               7               7               7               6               5
       clean       wonderful           comfy       impressed           right         pleased        positive
           5               4               4               4               4               3               3
        fast             hot         amazing             top           quiet          worked         enjoyed
           3               3               3               3               3               3               3
         wow         perfect      reasonable       amazingly       fantastic           ready           liked
           3               3               3               3               3               3               3
     comfort         quieter        pleasure          lovely          luxury           fresh          safely
           3               3               3               2               2               2               2
       enjoy           thank           super      incredible        cheapest    satisfactory            warm
           2               2               2               2               2               2               2
      afford       enjoyable          prefer            fine       delicious      incredibly         variety
           2               2               2               2               2               2               2
      modern    consistently         awesome          fairly          wonder        fabulous       perfectly
           2               2               2               2               2               2               2
  pleasantly          amazed          helped      enthusiasm straightforward       important           pride
           2               1               1               1               1               1               1
       crisp           sharp   complementary        promised   extraordinary          refund          secure
           1               1               1               1               1               1               1
      nicest       exemplary        upgraded           trust            soft           proud      convenient
           1               1               1               1               1               1               1
     happier         loyalty       fortunate         willing        low-cost     fortunately  astonishingly
           1               1               1               1               1               1               1
      honest       beautiful         cleaner           nicer            pros         support          praise
           1               1               1               1               1               1               1
  believable       gratitude            wise            neat       expansive   complimentary        guidance
           1               1               1               1               1               1               1
       happy         novelty       patiently        greatest            lead        cheerful          superb
           1               1               1               1               1               1               1
friendliness         clearly           amaze          proper     exceptional       advantage           clear
           1               1               1               1               1               1               1
    smoother     recommended         cheaper        flawless     improvement        superior            glad
           1               1               1               1               1               1               1
    reliable         immense       plentiful            safe           loved    entertaining          sturdy
           1               1               1               1               1               1               1
       ample       correctly           kudos         welcome        hallmark   knowledgeable        smoothly
           1               1               1               1               1               1               1
 significant           handy          luster      refreshing            pure        generous      hospitable
           1               1               1               1               1               1               1
    prefered       satisfied        punctual
           1               1               1
```

ACTIONABLE INSIGHTS & OVERALL INTERPRETATION OF RESULTS

After a thorough analysis of the survey dataset, we were able to see which variables have a direct relationship with the traveler's recommendation score and how it can influence their satisfaction. By keeping our business questions in mind, we saw that not all variables have had an effect on the customer's score and were able to choose key variables that can help improve Southeast Airline's customer churn.

Through our models, we were able to classify travelers into groups of Detractors who had a score less than 7 and Promoters who scored above an 8. Among those who were Detractors, we found that travelers between the age of 60-85 and travelers with a status of Blue seemed to give the lowest ratings, so we concluded that older individuals in the age variable and Blue travelers in the airline status variable were important factors that could be improved.

In addition, the likelihood to recommend scores fall when there is a flight delay, both for arrivals and departures. Interestingly enough, through our text mining process and exploring the negative words that contribute to low score, "delay" appeared multiple times. This is also another variable that could be used to improve customer churn as there are opportunities to improve their likelihood to recommend in the case of a flight delay.

Customers were also sensitive to price and we found the lower a traveler was sensitive to price, the higher their score was. Price definitely affects a customer's purchasing pattern and high prices can lead to lower scores.

Lastly, the type of travel whether it be for business or personal purposes, it accounted for 30% of the likelihood to recommend scores. Customers who flew for personal travel tended to score the lowest. This was another key factor that contributes to customer satisfaction and while it can be improved, it is a factor we want to maintain.

RECOMMENDATIONS

- **Senior Citizens**

Older travelers in the age group of 60-85 gave lower ratings. This is definitely a good aspect to consider in improving their rating score. We recommend for flight attendants to give extra attention to these customers such as checking up on them throughout the flight, providing them with a blanket, if they require accessibility, and making sure they are comfortable during and after the flight.

- **Flight Delays**

Travelers who experienced flight delays gave low rating scores. Although we can't control time and the necessary precautions that need to be taken before and after a flight, we do recommend compensating travelers whose flights were delayed. They can be compensated through a voucher that can be used for food/snacks at the airport food courts or an item at the airport gift shop. We also recommend if a departure flight is delayed to give them a complimentary snack.

- **Airline Status**

Travelers with a higher airline status (Silver, Gold) tend to give higher ratings. For those who have a Blue status, we recommend Southeast Airlines increase opportunities for Blue members to be able to upgrade their status such as earning double points when booking flights during a specific period of time (Christmas, Easter, vacation season, etc.). They can also earn more points for flying to certain destinations.

- **Pricing**

Price sensitivity was another factor into a traveler's recommendation score. We recommend to perhaps have lower prices for shorter distances or have promotions according to seasons (Christmas, summer vacation) that way travelers are inclined to purchase more and also earn points for their airline status.

- **Type of Travel**

A person flying for business or personal definitely accounts to customer satisfaction. A person flying business may be stressed with work so it's important to cater to their needs and make their flight comfortable. A family can be flying personal such as for vacation, so we recommend to also make their flight enjoyable as these are important customers. It would also be great provide vouchers for museums or broadway shows. This can also be a big opportunity for Southeast airlines to collaborate with local amenities in certain hotspot tourist location to increase brand awareness and gain customers through this incentive.