Airline Customer Satisfaction

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ADS 505: Applied Data Science for Business

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Github repository: https://github.com/linatnguyen/Predicting-Flight-Satisfaction-for-Airline-Passengers

Problem Statement

Flight satisfaction is one of the most important factors in having a successful airline that customers will happily return to. Using an flight satisfaction survey, 18 features will be used to create models that determine if a customer is satisfied or unsatisfied with their flight. Using information gathered from the model, it will be determined which customers will be satisfied with the service provided as well as what features contribute most heavily when determining if customers are satisfied or not.

Table of Contents

Exploratory Data Analysis

In [1]:
```
#importing packages
from pathlib import Path
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import shap

# import models
from sklearn.linear_model import LogisticRegressionCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.neural_network import MLPClassifier
from sklearn.preprocessing import MinMaxScaler

from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import confusion_matrix, plot_confusion_matrix, classification_report, accuracy_sc
ore
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import AdaBoostClassifier

from dmba import classificationSummary, gainsChart

from matplotlib.lines import Line2D

import warnings
warnings.filterwarnings("ignore")

%matplotlib inline
DATA = Path('.').resolve().parent / 'data'
```

In [2]:
```
#importing training and testing data
df = pd.read_csv('Desktop/train.csv')
dftest = pd.read_csv('Desktop/test.csv')
df.head()
```

Out[2]:

	Unnamed: 0	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	...	Inflight entertainment	On-board service	Leg room service
0	0	70172	Male	Loyal Customer	13	Personal Travel	Eco Plus	460	3	4	...	5	4	
1	1	5047	Male	disloyal Customer	25	Business travel	Business	235	3	2	...	1	1	
2	2	110028	Female	Loyal Customer	26	Business travel	Business	1142	2	2	...	5	4	
3	3	24026	Female	Loyal Customer	25	Business travel	Business	562	2	5	...	2	2	
4	4	119299	Male	Loyal Customer	61	Business travel	Business	214	3	3	...	3	3	

5 rows × 25 columns

In [3]:
```
dftest.head()
```

Out[3]:

	Unnamed: 0	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	...	Inflight entertainment	On-board service	Leg room service
0	0	19556	Female	Loyal Customer	52	Business travel	Eco	160	5	4	...	5	5	5
1	1	90035	Female	Loyal Customer	36	Business travel	Business	2863	1	1	...	4	4	4
2	2	12360	Male	disloyal Customer	20	Business travel	Eco	192	2	0	...	2	4	1
3	3	77959	Male	Loyal Customer	44	Business travel	Business	3377	0	0	...	1	1	1
4	4	36875	Female	Loyal Customer	49	Business travel	Eco	1182	2	3	...	2	2	2

5 rows × 25 columns

In [4]:
```
#view columns of training data
df.columns
```

Out[4]:
```
Index(['Unnamed: 0', 'id', 'Gender', 'Customer Type', 'Age', 'Type of Travel',
       'Class', 'Flight Distance', 'Inflight wifi service',
       'Departure/Arrival time convenient', 'Ease of Online booking',
       'Gate location', 'Food and drink', 'Online boarding', 'Seat comfort',
       'Inflight entertainment', 'On-board service', 'Leg room service',
       'Baggage handling', 'Checkin service', 'Inflight service',
       'Cleanliness', 'Departure Delay in Minutes', 'Arrival Delay in Minutes',
       'satisfaction'],
      dtype='object')
```

In [5]:
```
#view data distribution of each column in training data
df.describe()
```

Out[5]:

	Unnamed: 0	id	Age	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location
count	103904.000000	103904.000000	103904.000000	103904.000000	103904.000000	103904.000000	103904.000000	103904.000000
mean	51951.500000	64924.210502	39.379706	1189.448375	2.729683	3.060296	2.756901	2.976883
std	29994.645522	37463.812252	15.114964	997.147281	1.327829	1.525075	1.398929	1.277621
min	0.000000	1.000000	7.000000	31.000000	0.000000	0.000000	0.000000	0.000000
25%	25975.750000	32533.750000	27.000000	414.000000	2.000000	2.000000	2.000000	2.000000
50%	51951.500000	64856.500000	40.000000	843.000000	3.000000	3.000000	3.000000	3.000000
75%	77927.250000	97368.250000	51.000000	1743.000000	4.000000	4.000000	4.000000	4.000000
max	103903.000000	129880.000000	85.000000	4983.000000	5.000000	5.000000	5.000000	5.000000

In [6]:
```
#view columns of test data
dftest.columns
```

Out[6]:
```
Index(['Unnamed: 0', 'id', 'Gender', 'Customer Type', 'Age', 'Type of Travel',
       'Class', 'Flight Distance', 'Inflight wifi service',
       'Departure/Arrival time convenient', 'Ease of Online booking',
       'Gate location', 'Food and drink', 'Online boarding', 'Seat comfort',
       'Inflight entertainment', 'On-board service', 'Leg room service',
       'Baggage handling', 'Checkin service', 'Inflight service',
       'Cleanliness', 'Departure Delay in Minutes', 'Arrival Delay in Minutes',
       'satisfaction'],
      dtype='object')
```

In [7]:
```
#view data distribution of each column in test data
dftest.describe()
```

Out[7]:

	Unnamed: 0	id	Age	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	Food and drink
count	25976.000000	25976.000000	25976.000000	25976.000000	25976.000000	25976.000000	25976.000000	25976.000000	25976.00000
mean	12987.500000	65005.657992	39.620958	1193.788459	2.724746	3.046812	2.756775	2.977094	3.21535
std	7498.769632	37611.526647	15.135685	998.683999	1.335384	1.533371	1.412951	1.282133	1.33150
min	0.000000	17.000000	7.000000	31.000000	0.000000	0.000000	0.000000	1.000000	0.00000
25%	6493.750000	32170.500000	27.000000	414.000000	2.000000	2.000000	2.000000	2.000000	2.00000
50%	12987.500000	65319.500000	40.000000	849.000000	3.000000	3.000000	3.000000	3.000000	3.00000
75%	19481.250000	97584.250000	51.000000	1744.000000	4.000000	4.000000	4.000000	4.000000	4.00000
max	25975.000000	129877.000000	85.000000	4983.000000	5.000000	5.000000	5.000000	5.000000	5.00000

Data Preprocessing

Using the describe method we will take initial steps in our Data Exploration. We will be looking for variables that need normalization along with their distributions.

The next step in the preparation of the data is to give the variables reusable names, eliminating spaces and capitol letters. This will help with the probability of typing errors while scripting. After changing the labels, we will check the nunique values to check for variable with high amounts of unique variables, typically indicating columns that need to be binned

In [82]:
```
#renaming training data columns
df = df.rename(columns={'Customer Type':'customer_type',
                  'Type of Travel':'travel_type',
                  'Flight Distance':'flight_dist',
                  'Inflight wifi service':'wifi_service',
                  'Departure/Arrival time convenient':'time_convenience',
                  'Ease of Online booking':'booking_diff',
                  'Gate location':'gate_loc',
                  'Food and drink':'food_drink',
                  'Online boarding':'online_boarding',
                  'Seat comfort':'seat_comf',
                  'Inflight entertainment':'inflight_ent',
                  'On-board service':'onboard_serv',
                  'Leg room service':'legroom',
                  'Baggage handling':'baggage_care',
                  'Checkin service':'checkin',
                  'Inflight service':'inflight_serv',
                  'Departure Delay in Minutes':'dept_delay',
                  'Arrival Delay in Minutes':'arr_delay'
                 })
```

In [9]:
```
#renaming testing data columns
dftest = dftest.rename(columns={'Customer Type':'customer_type',
                  'Type of Travel':'travel_type',
                  'Flight Distance':'flight_dist',
                  'Inflight wifi service':'wifi_service',
                  'Departure/Arrival time convenient':'time_convenience',
                  'Ease of Online booking':'booking_diff',
                  'Gate location':'gate_loc',
                  'Food and drink':'food_drink',
                  'Online boarding':'online_boarding',
                  'Seat comfort':'seat_comf',
                  'Inflight entertainment':'inflight_ent',
                  'On-board service':'onboard_serv',
                  'Leg room service':'legroom',
                  'Baggage handling':'baggage_care',
                  'Checkin service':'checkin',
                  'Inflight service':'inflight_serv',
                  'Departure Delay in Minutes':'dept_delay',
                  'Arrival Delay in Minutes':'arr_delay'
                 })
```

In [10]:
```
# Number of unique values for training
for column in df.columns:
    print(column, df[column].nunique())
```

```
Unnamed: 0 103904
id 103904
Gender 2
customer_type 2
Age 75
travel_type 2
Class 3
flight_dist 3802
wifi_service 6
time_convenience 6
booking_diff 6
gate_loc 6
food_drink 6
online_boarding 6
seat_comf 6
inflight_ent 6
onboard_serv 6
legroom 6
baggage_care 5
checkin 6
inflight_serv 6
Cleanliness 6
dept_delay 446
arr_delay 455
satisfaction 2
```

In [11]:
```
# Number of unique values for testing
for column in dftest.columns:
    print(column, dftest[column].nunique())
```

```
Unnamed: 0 25976
id 25976
Gender 2
customer_type 2
Age 75
travel_type 2
Class 3
flight_dist 3281
wifi_service 6
time_convenience 6
booking_diff 6
gate_loc 5
food_drink 6
online_boarding 6
seat_comf 5
inflight_ent 6
onboard_serv 6
legroom 6
baggage_care 5
checkin 5
inflight_serv 6
Cleanliness 6
dept_delay 313
arr_delay 320
satisfaction 2
```

Using helper functions, we can access reusable code that we will use later for model metrics.The stat_print function will print each of the more usable metrics, allowing us to evaluate all models performances with one line of code. After the helper functions, checking for null values in both datasets will prevent errors while parsing data.

In [12]:
```
# Helper Functions

classes = ('Satisfied', 'Unsatisfied')

def check_na(df):
    if df.isna().sum().sum():
        print ('Missing values detected')
    else:
        print('No Missing Values Detected')

#Function for printing model evaluation metrics
def stat_print(train_y, pred_cancel):
    print('Recall Score    : ',recall_score(train_y, pred_cancel, average='weighted'))
    print('Accuracy Score  : ',accuracy_score(train_y, pred_cancel))
    print('F1 Score        : ',f1_score(train_y,pred_cancel))
    print('Precision Score : ',precision_score(train_y,pred_cancel))


def confusionMatrices(model, title):
    print(title + ' - training results')
    classificationSummary(train_y, model.predict(train_X), class_names=classes)
    print(title + ' - validation results')
    valid_pred = model.predict(valid_X)
    classificationSummary(valid_y, valid_pred, class_names=classes)
```

In [13]:
```
#view na for test data
check_na(dftest)
```

```
Missing values detected
```

In [14]:
```
#view na for train data
check_na(df)
```

```
Missing values detected
```

In [15]:
```
# Checking for na values
df.isna().sum()
```

Out[15]:
```
Unnamed: 0            0
id                    0
Gender                0
customer_type         0
Age                   0
travel_type           0
Class                 0
flight_dist           0
wifi_service          0
time_convenience      0
booking_diff          0
gate_loc              0
food_drink            0
online_boarding       0
seat_comf             0
inflight_ent          0
onboard_serv          0
legroom               0
baggage_care          0
checkin               0
inflight_serv         0
Cleanliness           0
dept_delay            0
arr_delay           310
satisfaction          0
dtype: int64
```

In [16]:
```
#view na for testing
dftest.isna().sum()
```

Out[16]:
```
Unnamed: 0           0
id                   0
Gender               0
customer_type        0
Age                  0
travel_type          0
Class                0
flight_dist          0
wifi_service         0
time_convenience     0
booking_diff         0
gate_loc             0
food_drink           0
online_boarding      0
seat_comf            0
inflight_ent         0
onboard_serv         0
legroom              0
baggage_care         0
checkin              0
inflight_serv        0
Cleanliness          0
dept_delay           0
arr_delay           83
satisfaction         0
dtype: int64
```

In [17]:
```
#sorting values by 'dept_delay' in training
df.sort_values(by='dept_delay', ascending=False)
```

Out[17]:

	Unnamed: 0	id	Gender	customer_type	Age	travel_type	Class	flight_dist	wifi_service	time_convenience	...	inflight_ent
83741	83741	73471	Female	Loyal Customer	47	Personal Travel	Eco	1120	2	2	...	2
6744	6744	69661	Male	Loyal Customer	32	Business travel	Business	2916	2	2	...	3
61310	61310	4903	Male	Loyal Customer	49	Business travel	Business	1959	1	1	...	4
72206	72206	78300	Male	Loyal Customer	30	Personal Travel	Eco	1598	1	4	...	5
80182	80182	8345	Male	Loyal Customer	47	Business travel	Business	2187	4	5	...	5
...	...	...	...	...	...	...	...	...	...	...	...	...
44435	44435	95245	Male	Loyal Customer	49	Personal Travel	Eco	189	3	1	...	1
44434	44434	58151	Female	Loyal Customer	42	Business travel	Business	3239	5	5	...	4
44432	44432	6253	Female	Loyal Customer	8	Personal Travel	Eco	413	2	5	...	5
44431	44431	48424	Male	Loyal Customer	47	Business travel	Eco	819	4	2	...	5
103903	103903	62567	Male	Loyal Customer	27	Business travel	Business	1723	1	3	...	1

103904 rows × 25 columns

In [18]:
```
#sorting values for testing data in testing
dftest.sort_values(by = 'dept_delay', ascending = False)
```

Out[18]:

	Unnamed: 0	id	Gender	customer_type	Age	travel_type	Class	flight_dist	wifi_service	time_convenience	...	inflight_ent
17429	17429	73482	Male	Loyal Customer	8	Personal Travel	Eco	1144	2	5	...	4
1655	1655	63689	Female	Loyal Customer	39	Business travel	Business	1696	1	4	...	2
19000	19000	2247	Female	Loyal Customer	42	Business travel	Business	693	2	1	...	2
10072	10072	6062	Female	Loyal Customer	45	Personal Travel	Eco	630	1	4	...	3
21907	21907	90926	Female	Loyal Customer	24	Business travel	Business	2507	2	5	...	3
...	...	...	...	...	...	...	...	...	...	...	...	...
11057	11057	31858	Female	Loyal Customer	35	Personal Travel	Eco	2640	2	1	...	5
11055	11055	91300	Male	Loyal Customer	55	Business travel	Business	3219	4	4	...	4
11048	11048	31996	Female	Loyal Customer	57	Personal Travel	Business	216	3	4	...	5
11046	11046	29265	Female	Loyal Customer	27	Business travel	Eco	859	5	3	...	5
25975	25975	34799	Female	Loyal Customer	42	Personal Travel	Eco	264	2	5	...	1

25976 rows × 25 columns

Filling in the missing values with relatively close values that match the pattern of arr_delay. The effect of filling in these missing values should be unnoticable as the total amount of records missing the values are insignificant in size.

In [19]:
```
# Replacing arrival delay missing values based on the departing delay
df['arr_delay'].fillna(value=df['dept_delay'] -5,inplace=True)
dftest['arr_delay'].fillna(value=dftest['dept_delay'] -5,inplace=True)
```

Taking the minimum and maximum values, we turned the flight distance variable into a categorical variable to pull more correlation out of the variable. This is the only feature creation we had to do within this dataset. After we bin we will check the correlation of variables using heatmaps and correlation tables.

In [20]:
```
#finding min/max values of 'flight_dist' train
min_value = df['flight_dist'].min()
max_value = df['flight_dist'].max()
print(min_value)
print(max_value)
```

```
31
4983
```

In [21]:
```
#finding min/max values of 'flight_dist' test
min_valuetest = dftest['flight_dist'].min()
max_valuetest = dftest['flight_dist'].max()
print(min_valuetest)
print(max_valuetest)
```

```
31
4983
```

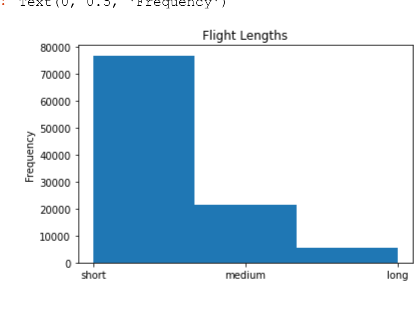
In [22]:
```
# Turning flight length into a binned variable
bins = np.linspace(min_value,max_value,4)
bins.round(2)
bins = np.linspace(min_value,max_value,4)
bins.round(2)

labels = ['short', 'medium', 'long']
```

In [23]:
```
# Turning flight length into a binned variable
bins = np.linspace(min_valuetest,max_valuetest,4)
bins.round(2)
bins = np.linspace(min_valuetest,max_valuetest,4)
bins.round(2)
dftest['flight_length'] = pd.cut(dftest['flight_dist'], bins=bins, labels=labels, include_lowest=True)
```

In [24]:
```
#create bins for histogram
df['flight_length'] = pd.cut(df['flight_dist'], bins=bins, labels=labels, include_lowest=True)
```

In [25]:
```
#creating histogram for Flight Lengths
plt.hist(df['flight_length'], bins=3)
plt.title('Flight Lengths')
plt.ylabel('Frequency')
```

Out[25]:
```
Text(0, 0.5, 'Frequency')
```



Here we are converting nominal data into categorical. This will also aid in correlation. After doing this, the original columns will be dropped from the dataset.

In [26]:
```
## Creating dummy variable for Gender
# Male:0, Female:1
df.loc[df['Gender'] == 'Male', 'flight_dummy'] = 0
df.loc[df['Gender'] == 'Female', 'flight_dummy'] = 1

## Creating dummy variable for customer type
# disloyal:0, loyal:1
df.loc[df['customer_type'] == 'Loyal Customer', 'flight_dummy'] = 1
df.loc[df['customer_type'] == 'disloyal Customer', 'flight_dummy'] = 0

## Creating dummy variable for travel type
# personal:0, business:1
df.loc[df['travel_type'] == 'Business travel', 'flight_dummy'] = 1
df.loc[df['travel_type'] == 'Personal Travel', 'flight_dummy'] = 0


## Creating dummy variable for flight length
#1:short, 2:medium, 3:long
df.loc[df['flight_length'] == 'short', 'flight_dummy'] = 1
df.loc[df['flight_length'] == 'medium', 'flight_dummy'] = 2
df.loc[df['flight_length'] == 'long', 'flight_dummy'] = 3

## Creating dummy variable for Class
#1:Eco, 2:Eco Plus 3:Business
df.loc[df['Class'] == 'Eco', 'class_dummy'] = 1
df.loc[df['Class'] == 'Eco Plus', 'class_dummy'] = 2
df.loc[df['Class'] == 'Business', 'class_dummy'] = 3


## Creating dummy variable for satisfaction (1 for satisfied)
df.loc[df['satisfaction'] == 'neutral or dissatisfied', 'satisfaction_dummy'] = 0
df.loc[df['satisfaction'] == 'satisfied', 'satisfaction_dummy'] = 1
```

In [27]:
```
## Creating dummy variable for Gender
# Male:0, Female:1
dftest.loc[dftest['Gender'] == 'Male', 'flight_dummy'] = 0
dftest.loc[dftest['Gender'] == 'Female', 'flight_dummy'] = 1

## Creating dummy variable for customer type
# disloyal:0, loyal:1
dftest.loc[dftest['customer_type'] == 'Loyal Customer', 'flight_dummy'] = 1
dftest.loc[dftest['customer_type'] == 'disloyal Customer', 'flight_dummy'] = 0

## Creating dummy variable for travel type
# personal:0, business:1
dftest.loc[dftest['travel_type'] == 'Business travel', 'flight_dummy'] = 1
dftest.loc[dftest['travel_type'] == 'Personal Travel', 'flight_dummy'] = 0


## Creating dummy variable for flight length
#1:short, 2:medium, 3:long
dftest.loc[dftest['flight_length'] == 'short', 'flight_dummy'] = 1
dftest.loc[dftest['flight_length'] == 'medium', 'flight_dummy'] = 2
dftest.loc[dftest['flight_length'] == 'long', 'flight_dummy'] = 3

## Creating dummy variable for Class
#1:Eco, 2:Eco Plus 3:Business
dftest.loc[dftest['Class'] == 'Eco', 'class_dummy'] = 1
dftest.loc[dftest['Class'] == 'Eco Plus', 'class_dummy'] = 2
dftest.loc[dftest['Class'] == 'Business', 'class_dummy'] = 3


## Creating dummy variable for satisfaction (1 for satisfied)
dftest.loc[dftest['satisfaction'] == 'neutral or dissatisfied', 'satisfaction_dummy'] = 0
dftest.loc[dftest['satisfaction'] == 'satisfied', 'satisfaction_dummy'] = 1
```

In [28]:
```
#dropping 'travel_type', 'customer_type', 'flight_dist', 'flight_length', 'satisfaction', 'Class', 'Gen
der' from train
df = df.drop(columns=['travel_type','customer_type','flight_dist','flight_length','satisfaction','Clas
s','Gender'])

df.head(30)
```

Out[28]:

	Unnamed: 0	id	Age	wifi_service	time_convenience	booking_diff	gate_loc	food_drink	online_boarding	seat_comf	...	legroom
0	0	70172	13	3	4	3	1	5	3	5	...	3
1	1	5047	25	3	2	3	3	1	3	1	...	5
2	2	110028	26	2	2	2	2	5	5	5	...	3
3	3	24026	25	2	5	5	5	2	2	2	...	5
4	4	119299	61	3	3	3	3	4	5	5	...	4
5	5	111157	26	3	4	2	1	1	2	1	...	4
6	6	82113	47	2	4	2	3	2	2	2	...	3
7	7	96462	52	4	3	4	4	5	5	5	...	5
8	8	79485	41	1	2	2	2	4	3	3	...	2
9	9	65725	20	3	3	3	4	2	3	3	...	3
10	10	34991	24	4	5	5	4	2	5	2	...	3
11	11	51412	12	2	4	2	2	1	2	1	...	2
12	12	98628	53	1	4	4	4	1	1	1	...	1
13	13	83502	33	4	2	4	3	4	4	4	...	5
14	14	95789	26	3	2	3	2	2	3	2	...	3
15	15	100580	13	2	1	2	3	4	2	1	...	1
16	16	71142	26	3	3	3	3	4	4	4	...	3
17	17	127461	41	4	4	2	4	4	4	4	...	5
18	18	70354	45	4	4	4	4	3	4	5	...	5
19	19	66246	38	2	3	2	5	3	3	3	...	2
20	20	39076	9	2	4	2	4	2	2	1	...	5
21	21	22434	17	3	1	3	3	5	3	5	...	5
22	22	43510	43	3	5	3	5	5	4	5	...	3
23	23	114090	58	4	5	4	5	4	3	4	...	4
24	24	105420	23	5	0	5	1	1	5	1	...	5
25	25	102956	57	4	4	4	1	5	4	5	...	2
26	26	18510	33	1	1	1	1	1	5	3	...	4
27	27	14925	49	4	4	4	4	2	2	1	...	4
28	28	118319	36	3	1	1	1	1	2	1	...	3
29	29	75460	22	3	2	3	3	3	2	1	...	4

30 rows × 22 columns

In [29]:
```
#dropping 'travel_type', 'customer_type', 'flight_dist', 'flight_length', 'satisfaction', 'Class', 'Gen
der' from test
dftest = dftest.drop(columns=['travel_type','customer_type','flight_dist','flight_length','satisfactio
n','Class','Gender'])

dftest.head(30)
```

Out[29]:

	Unnamed: 0	id	Age	wifi_service	time_convenience	booking_diff	gate_loc	food_drink	online_boarding	seat_comf	...	legroom
0	0	19556	52	5	4	3	4	3	4	3	...	5
1	1	90035	36	1	1	3	1	5	4	5	...	4
2	2	12360	20	2	0	2	4	2	2	2	...	1
3	3	77959	44	0	0	0	2	3	4	4	...	1
4	4	36875	49	2	3	4	3	4	1	2	...	2
5	5	39177	16	3	3	3	3	5	5	3	...	3
6	6	79433	77	5	5	5	5	3	5	5	...	5
7	7	97286	43	2	2	2	2	4	4	5	...	4
8	8	27508	47	5	2	2	2	5	5	5	...	2
9	9	62482	46	2	2	2	2	3	4	4	...	4
10	10	47583	47	4	1	1	1	5	1	5	...	4
11	11	115550	33	2	5	5	5	1	3	4	...	2
12	12	119987	46	5	5	5	5	4	5	5	...	5
13	13	42141	60	1	1	4	1	5	5	4	...	5
14	14	2274	52	2	2	2	2	5	5	4	...	4
15	15	22470	50	3	4	0	3	2	0	2	...	2
16	16	124915	31	2	5	5	5	2	2	2	...	3
17	17	17836	52	5	4	5	3	4	5	4	...	5
18	18	76872	43	3	4	3	1	4	4	5	...	3
19	19	64287	50	5	5	5	5	4	5	4	...	5
20	20	63995	60	4	4	4	4	2	4	5	...	5
21	21	75855	43	3	4	3	4	2	3	2	...	2
22	22	106181	55	1	2	4	3	4	4	4	...	3
23	23	44304	25	4	4	4	4	4	4	4	...	5
24	24	82602	30	4	3	5	3	2	5	2	...	2
25	25	7823	62	3	5	3	4	2	3	2	...	5
26	26	127781	24	4	1	4	4	2	2	2	...	5
27	27	34501	22	4	1	1	1	4	4	4	...	4
28	28	121658	44	3	5	3	3	5	4	5	...	5
29	29	20219	51	4	3	3	3	4	4	4	...	2

30 rows × 22 columns

In [30]:
```
#view correlations in train
df.corr()
```

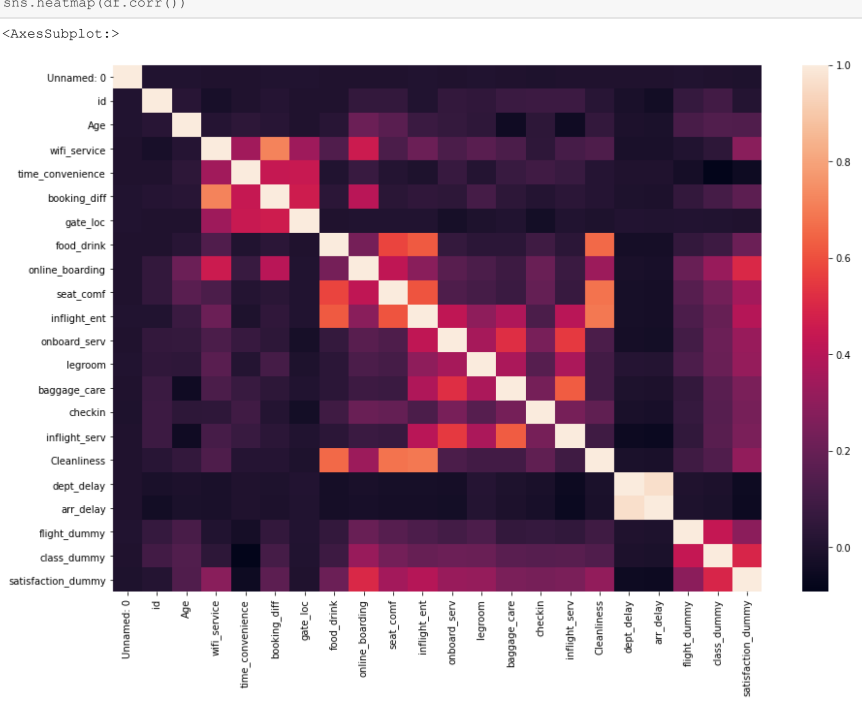
Out[30]:

	Unnamed: 0	id	Age	wifi_service	time_convenience	booking_diff	gate_loc	food_drink	online_boarding
Unnamed: 0	1.000000	0.002991	0.004786	-0.002490	0.000739	0.001913	0.005073	-0.002162	0.001002
id	0.002991	1.000000	0.022857	-0.021276	-0.002110	0.014163	-0.000606	0.001063	0.055477
Age	0.004786	0.022857	1.000000	0.017859	0.038125	0.024842	-0.001330	0.023000	0.208939
wifi_service	-0.002490	-0.021276	0.017859	1.000000	0.343845	0.715856	0.336248	0.134718	0.456970
time_convenience	0.000739	-0.002110	0.038125	0.343845	1.000000	0.436961	0.444757	0.004906	0.070119
booking_diff	0.001913	0.014163	0.024842	0.715856	0.436961	1.000000	0.458655	0.031873	0.404074
gate_loc	0.005073	-0.000606	-0.001330	0.336248	0.444757	0.458655	1.000000	-0.001159	0.001688
food_drink	-0.002162	0.001063	0.023000	0.134718	0.004906	0.031873	-0.001159	1.000000	0.234468
online_boarding	0.001002	0.055477	0.208939	0.456970	0.070119	0.404074	0.001688	0.234468	1.000000
seat_comf	0.000044	0.052903	0.160277	0.122658	0.011344	0.030014	0.003669	0.574556	0.420211
inflight_ent	0.001363	0.002300	0.076444	0.209321	-0.004861	0.047032	0.003517	0.622512	0.285066
onboard_serv	0.000813	0.055241	0.057594	0.121500	0.068882	0.038833	-0.028373	0.059073	0.155443
legroom	0.004052	0.044634	0.040583	0.160473	0.012441	0.107601	-0.005873	0.032498	0.123950
baggage_care	-0.000526	0.074940	-0.047529	0.120923	0.072126	0.038762	0.002313	0.034746	0.083280
checkin	-0.004321	0.079273	0.035482	0.043193	0.093333	0.011081	-0.035427	0.087299	0.204462
inflight_serv	-0.000134	0.079346	-0.049427	0.110441	0.073318	0.035272	0.001681	0.033993	0.074573
Cleanliness	-0.001117	0.024965	0.053611	0.132698	0.014292	0.016179	-0.003830	0.657760	0.331517
dept_delay	-0.000045	-0.019546	-0.010152	-0.017402	0.001005	-0.006371	0.005467	-0.029926	-0.018982
arr_delay	0.000584	-0.037310	-0.012133	-0.019035	-0.000663	-0.008045	0.005097	-0.032462	-0.022382
flight_dummy	0.002144	0.064137	0.114496	0.004179	-0.031174	0.054428	0.007898	0.052659	0.199445
class_dummy	0.000798	0.095698	0.140565	0.036279	-0.092788	0.106391	0.004150	0.085908	0.322924
satisfaction_dummy	-0.004731	0.013734	0.137167	0.284245	-0.051601	0.171705	0.000682	0.209936	0.503557

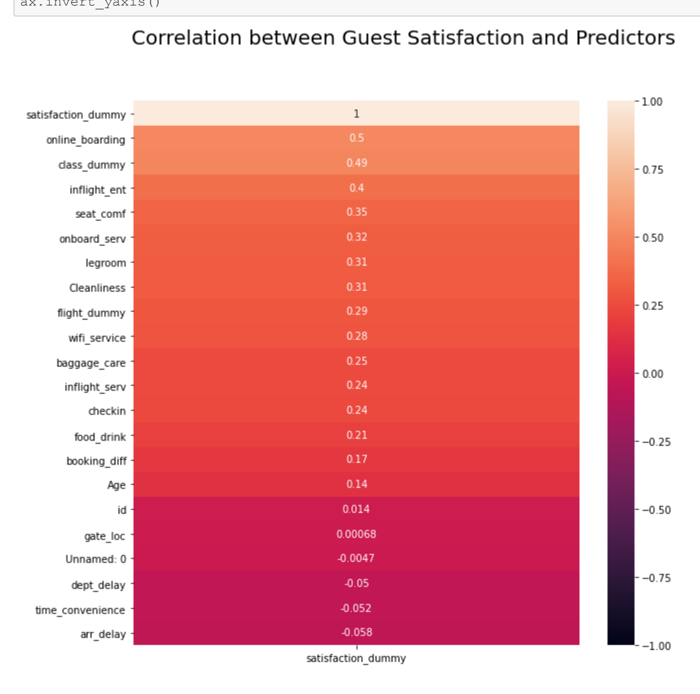
22 rows × 22 columns

In [31]:
```
#training heatmap to view correlations between predictors.
#dept_delay, and arr_delay are highly correlated as expected. There is also some correlation between pr
edictors that describe the on-board experience of customers, like baggage_care and onboard_serv, food_d
rink and Cleanliness, which is also expected.
plt.figure(figsize=(15,10))
sns.heatmap(df.corr())
```

Out[31]:
```
<AxesSubplot:>
```



```
In [32]: #Viewing correlatino between guest satisfaction and predictors.
#We see that the top 5 predictors that are most correlated with customer satisfaction are online_boarding, class, inflight_ent, seat_comf, and online_serv.
#The lest correlated predictors with customer satisfaction are arr_delay, time_convenience, dept_delay, Unnamed: 0, and gate_loc. This is observation is valid because customers are less satisfied when they are inconvienced with flight delays or flight times.
fig, ax = plt.subplots(figsize=(10,10))
fig.suptitle('Correlation between Guest Satisfaction and Predictors',fontsize=20)
ax=sns.heatmap(df.corr()[['satisfaction_dummy']].sort_values("satisfaction_dummy"),vmax=1, vmin=-1, cmap="rocket", annot=True, ax=ax);
ax.invert_yaxis()
```

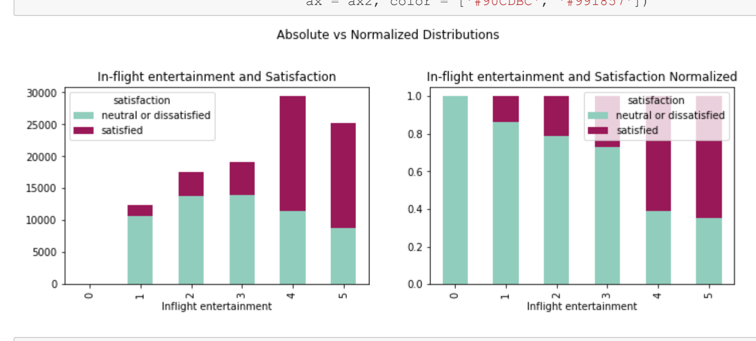


Distribution of highly correlated variables

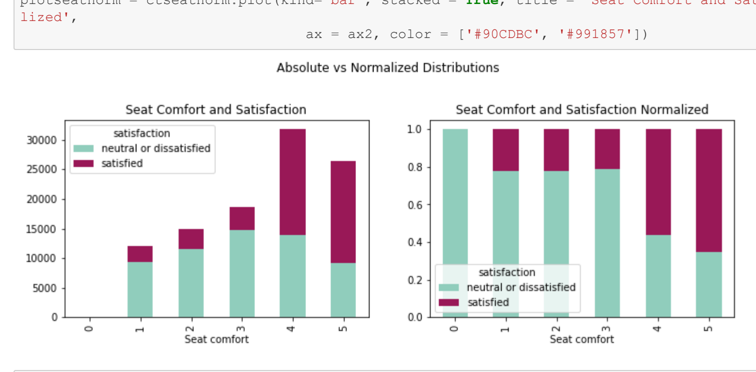
```
In [33]: #plotting stacked and normalized stacked barplots of online boarding vs. satisfaction, using the original data without dummy variables
dfog = pd.read_csv('Desktop/train.csv')
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(221)
ax2 = fig.add_subplot(222)
fig.suptitle('Absolute vs Normalized Distributions')
ctonline = pd.crosstab(dfog['Online boarding'], dfog['satisfaction'])
ctonlinenorm = ctonline.div(ctonline.sum(1), axis=0)

plotonline = ctonline.plot(kind='bar', stacked = True, title = 'Online Boarding and Satisfaction',
                          ax = ax1, color = ['#90CDBC', '#991857'])

plotonlinenorm = ctonlinenorm.plot(kind='bar', stacked = True, title = 'Online Boarding and Satisfaction Normalized',
                                  ax = ax2, color = ['#90CDBC', '#991857'])
```


```
In [34]: #plotting stacked and normalized stacked barplots class satisfaction
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(221)
ax2 = fig.add_subplot(222)
fig.suptitle('Absolute vs Normalized Distributions')
ctclass = pd.crosstab(dfog['Class'], dfog['satisfaction'])
ctclassnorm = ctclass.div(ctclass.sum(1), axis=0)

plotclass = ctclass.plot(kind='bar', stacked = True, title = 'Class and Satisfaction',
                          ax = ax1, color = ['#90CDBC', '#991857'])

plotclassnorm = ctclassnorm.plot(kind='bar', stacked = True, title = 'Class and Satisfaction Normalized',
                                  ax = ax2, color = ['#90CDBC', '#991857'])
```


```
In [35]: #plotting stacked and normalized stacked of in-flight entertainment and satisfaction
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(221)
ax2 = fig.add_subplot(222)
fig.suptitle('Absolute vs Normalized Distributions')
ctentertain = pd.crosstab(dfog['Inflight entertainment'], dfog['satisfaction'])
ctentertainnorm = ctentertain.div(ctentertain.sum(1), axis=0)

plotentertain = ctentertain.plot(kind='bar', stacked = True, title = 'In-flight entertainment and Satisfaction',
                          ax = ax1, color = ['#90CDBC', '#991857'])

plotentertainnorm = ctentertainnorm.plot(kind='bar', stacked = True, title = 'In-flight entertainment and Satisfaction Normalized',
                                  ax = ax2, color = ['#90CDBC', '#991857'])
```




```
In [36]: #plotting stacked and normalized stacked barplot of seat comfort and satisfaction
fig = plt.figure(figsize=(12,8))
ax1 = fig.add_subplot(221)
ax2 = fig.add_subplot(222)
fig.suptitle('Absolute vs Normalized Distributions')
ctseat = pd.crosstab(dfog['Seat comfort'], dfog['satisfaction'])
ctseatnorm = ctseat.div(ctseat.sum(1), axis=0)

plotseat = ctseat.plot(kind='bar', stacked = True, title = 'Seat Comfort and Satisfaction',
                          ax = ax1, color = ['#90CDBC', '#991857'])

plotseatnorm = ctseatnorm.plot(kind='bar', stacked = True, title = 'Seat Comfort and Satisfaction Normalized',
                                  ax = ax2, color = ['#90CDBC', '#991857'])
```




```
In [37]: #plot distribution for all columns for training
for i, col in enumerate(df.columns):
    plt.figure(i)
    sns.histplot(df[col])
```

Data Splitting

```
In [38]: #split data into predictors and outcome
predictors = ['Age', 'wifi_service','booking_diff', 'food_drink', 'online_boarding','seat_comf',
              'inflight_ent', 'onboard_serv', 'legroom', 'baggage_care', 'checkin', 'inflight_serv',
              'Cleanliness','flight_dummy', 'class_dummy']
outcome = ['satisfaction_dummy']

#split data into train/test
train_X = df[predictors]
train_y = df[outcome]
valid_X = dftest[predictors]
valid_y = dftest[outcome]
```

Classification Models

The models that we will use here include: Logistic Regression, Decision Tree, Random Forest, K-Nearest Neighbors, Bagging, AdaBoost, and Neural Network.

Logistic Regression Model

```
In [39]: #l2: uses Ridge regression, which adds squared magnitude of coefficient as a penalty term to the loss function
#cv = 5: to estimate the optimal parameters of the model
#solver = 'saga': penalties of elasticnet, l1, l2, and none
#max_iter = 110000: max iterations until solvers can converage
logit = LogisticRegressionCV(penalty='l2', solver='saga', cv=5, max_iter=110000, random_state=3).fit(train_X, train_y.values.ravel())
```

```
In [40]: logit_confusion = confusionMatrices(logit, 'Logistic regression')
```

```
Logistic regression - training results
Confusion Matrix (Accuracy 0.8434)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       51747        7132
Unsatisfied        9140       35885
Logistic regression - validation results
Confusion Matrix (Accuracy 0.8381)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       12722        1851
Unsatisfied        2354        9049
```

The training accuracy is 84.34% while the testing accuracy is 83.81%, which is not a huge difference showing that the model was not overtrained.

Decision Tree

```
In [41]: #Unprunned decision tree
dtree = DecisionTreeClassifier(random_state=3).fit(train_X, train_y)
tree_confusion = confusionMatrices(dtree, 'Decision Tree')
```

```
Decision Tree - training results
Confusion Matrix (Accuracy 0.9996)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       58878           1
Unsatisfied          43       44982
Decision Tree - validation results
Confusion Matrix (Accuracy 0.9265)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       13595         978
Unsatisfied         932       10471
```

The training accuracy is 99.96% and the test accuracy is 92.65%.

Bagging

```
In [42]: #Using the decision classification tree as the base estimator, bagging is used to improve metrics
bagging = BaggingClassifier(dtree, random_state=3, max_samples = 0.5, max_features = 0.5)
bagging.fit(train_X, train_y)
bag_confusion = confusionMatrices(bagging, 'Bagging')
```

```
Bagging - training results
Confusion Matrix (Accuracy 0.9552)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       57173        1706
Unsatisfied        2945       42080
Bagging - validation results
Confusion Matrix (Accuracy 0.9207)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       13725         848
Unsatisfied        1213       10190
```

Training accuracy is 95.52% and test accuracy is 92.07%. Decision trees with bagging did not help with improvement in the accuracy.

Adaboost

```
In [43]: #Using the decision classification tree as the base estimator, adaboost is used to improve metrics
adaboost = AdaBoostClassifier(n_estimators = 100, base_estimator = dtree, random_state=3)
adaboost.fit(train_X, train_y)
ada_confusion = confusionMatrices(adaboost, 'Adaboost')
```

```
Adaboost - training results
Confusion Matrix (Accuracy 0.9996)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       58877           2
Unsatisfied          42       44983
Adaboost - validation results
Confusion Matrix (Accuracy 0.9423)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       13941         632
Unsatisfied         867       10536
```

Training accuracy is 99.96% and testing accuracy is 94.23%. Adaboost improved accuracy in the decision tree.

Random Forest

```
In [44]: rf = RandomForestClassifier(n_estimators=100, random_state=3).fit(train_X, train_y.values.ravel())
```

```
In [45]: forest_confusion = confusionMatrices(rf, 'Random Forest')
```

```
Random Forest - training results
Confusion Matrix (Accuracy 0.9996)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       58861          18
Unsatisfied          26       44999
Random Forest - validation results
Confusion Matrix (Accuracy 0.9483)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       14076         497
Unsatisfied         846       10557
```

The training accuracy is 99.96% and 94.83%. Random forest performed better than decision tree classifier by 2%.

k-NN

```
In [46]: #finding optimal k value
results = []
values = [1, 3, 5, 7, 9, 11, 13, 15, 17]
for k in values:
    knn = KNeighborsClassifier(n_neighbors=k).fit(train_X, train_y)
    results.append({
        'k': k,
        'accuracy': accuracy_score(valid_y, knn.predict(valid_X))
    })
results = pd.DataFrame(results)
results
```

Out[46]:

	k	accuracy
0	1	0.898945
1	3	0.908646
2	5	0.910956
3	7	0.910725
4	9	0.909147
5	11	0.909493
6	13	0.908300
7	15	0.909070
8	17	0.906375

```
In [47]: #creating knn algorithm with n_neighbors = 5
knn = KNeighborsClassifier(n_neighbors=5).fit(train_X, train_y)
knn_confusion = confusionMatrices(knn, 'k-NN Model')
```

```
k-NN Model - training results
Confusion Matrix (Accuracy 0.9360)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       56911        1968
Unsatisfied        4687       40338
k-NN Model - validation results
Confusion Matrix (Accuracy 0.9110)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       13843         730
Unsatisfied        1583        9820
```

The training accuracy is 93.60% and test accuracy is 91.10%.

Linear Discriminant Analysis

```
In [48]: ldaModel = LinearDiscriminantAnalysis()
ldaModel.fit(train_X, train_y)
ldaConfusion = confusionMatrices(ldaModel, 'Linear Discriminant Analysis')
```

```
Linear Discriminant Analysis - training results
Confusion Matrix (Accuracy 0.8387)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       51290        7589
Unsatisfied        9175       35850
Linear Discriminant Analysis - validation results
Confusion Matrix (Accuracy 0.8334)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied       12600        1973
Unsatisfied        2354        9049
```

The training accuracy is 83.87% and the testing accuracy is 83.34%.

Neural Network

```
In [49]: #scaling training features to 1.0
scaleInput = MinMaxScaler()
scaleInput.fit(train_X * 1.0)

#hidden_layer_sizes = 10: number of neurons in the ith hidden layer
#activation: logistic sigmoid function
#solver: weight optimization using stocastic gradient descent
neuralNet = MLPClassifier(hidden_layer_sizes = (10),
                          activation = 'logistic',
                          solver = 'sgd',
                          max_iter = 3000,
                          random_state = 1)

neuralNet.fit(scaleInput.transform(train_X), train_y)
NNConfusion = confusionMatrices(neuralNet, 'Neural Network')
```

```
Neural Network - training results
Confusion Matrix (Accuracy 0.4926)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied        7786       51093
Unsatisfied        1631       43394
Neural Network - validation results
Confusion Matrix (Accuracy 0.4983)

             Prediction
     Actual   Satisfied Unsatisfied
  Satisfied        1974       12599
Unsatisfied         432       10971
```

The neural network performs poorly on this data, with 49.26% accuracy on the training segment and 49.83% accuracy on the test segment.

Results

Models are evaluated using the test data for accuracy, precision, recall, f1 score, area under ROC curve, and cumulative gains.

In [50]:
```python
#Decision Tree
dtree_pred_test = dtree.predict(valid_X)
print('Accuracy score:')
print(accuracy_score(valid_y,dtree_pred_test))
dtree_roc = metrics.roc_curve(valid_y, dtree_pred_test)
dtree_auc = metrics.auc(dtree_roc[0], dtree_roc[1])
dtree_plot = metrics.RocCurveDisplay(dtree_roc[0], dtree_roc[1],
roc_auc=dtree_auc, estimator_name='Decision Tree')
```

```
Accuracy score:
0.9264705882352942
```

In [51]:
```python
print(classification_report(valid_y, dtree_pred_test))
```

```
              precision    recall  f1-score   support

         0.0       0.94      0.93      0.93     14573
         1.0       0.91      0.92      0.92     11403

    accuracy                           0.93     25976
   macro avg       0.93      0.93      0.93     25976
weighted avg       0.93      0.93      0.93     25976
```

In [52]:
```python
#Bagging
bagging_pred_test = bagging.predict(valid_X)
print(accuracy_score(valid_y,bagging_pred_test))
bagging_roc = metrics.roc_curve(valid_y, bagging_pred_test)
bagging_auc = metrics.auc(bagging_roc[0], bagging_roc[1])
bagging_plot = metrics.RocCurveDisplay(bagging_roc[0], bagging_roc[1],
roc_auc=bagging_auc, estimator_name='Bagging')
```

```
0.9206575300277179
```

In [53]:
```python
print(classification_report(valid_y, bagging_pred_test))
```

```
              precision    recall  f1-score   support

         0.0       0.92      0.94      0.93     14573
         1.0       0.92      0.89      0.91     11403

    accuracy                           0.92     25976
   macro avg       0.92      0.92      0.92     25976
weighted avg       0.92      0.92      0.92     25976
```

In [54]:
```python
#Adaboost
adaboost_pred_test = adaboost.predict(valid_X)
print(accuracy_score(valid_y,adaboost_pred_test))
adaboost_roc = metrics.roc_curve(valid_y, adaboost_pred_test)
adaboost_auc = metrics.auc(adaboost_roc[0], adaboost_roc[1])
adaboost_plot = metrics.RocCurveDisplay(adaboost_roc[0], adaboost_roc[1],
roc_auc=adaboost_auc, estimator_name='Adaboost')
```

```
0.9422928857406837
```

In [55]:
```python
print(classification_report(valid_y, adaboost_pred_test))
```

```
              precision    recall  f1-score   support

         0.0       0.94      0.96      0.95     14573
         1.0       0.94      0.92      0.93     11403

    accuracy                           0.94     25976
   macro avg       0.94      0.94      0.94     25976
weighted avg       0.94      0.94      0.94     25976
```

In [56]:
```python
#Logistic Regression
logit_pred_test = logit.predict(valid_X)
print(accuracy_score(valid_y,logit_pred_test))
logit_roc = metrics.roc_curve(valid_y, logit_pred_test)
logit_auc = metrics.auc(logit_roc[0], logit_roc[1])
logit_plot = metrics.RocCurveDisplay(logit_roc[0], logit_roc[1],
roc_auc=logit_auc, estimator_name='Logistic Regression')
```

```
0.83811980289498
```

In [57]:
```python
print(classification_report(valid_y, logit_pred_test))
```

```
              precision    recall  f1-score   support

         0.0       0.84      0.87      0.86     14573
         1.0       0.83      0.79      0.81     11403

    accuracy                           0.84     25976
   macro avg       0.84      0.83      0.83     25976
weighted avg       0.84      0.84      0.84     25976
```

In [58]:
```python
#Random Forest
rf_pred_test = rf.predict(valid_X)
print(accuracy_score(valid_y,rf_pred_test))
rf_roc = metrics.roc_curve(valid_y, rf_pred_test)
rf_auc = metrics.auc(rf_roc[0], rf_roc[1])
rf_plot = metrics.RocCurveDisplay(rf_roc[0], logit_roc[1],
roc_auc=rf_auc, estimator_name='Random Forest')
```

```
0.9482984293193717
```

In [59]:
```python
print(classification_report(valid_y, rf_pred_test))
```

```
              precision    recall  f1-score   support

         0.0       0.94      0.97      0.95     14573
         1.0       0.96      0.93      0.94     11403

    accuracy                           0.95     25976
   macro avg       0.95      0.95      0.95     25976
weighted avg       0.95      0.95      0.95     25976
```

In [60]:
```python
#k-NN
knn_pred_test = knn.predict(valid_X)
print(accuracy_score(valid_y,knn_pred_test))
knn_roc = metrics.roc_curve(valid_y, knn_pred_test)
knn_auc = metrics.auc(knn_roc[0], knn_roc[1])
knn_plot = metrics.RocCurveDisplay(knn_roc[0], knn_roc[1],
roc_auc=knn_auc, estimator_name='k-Nearest Neighbors')
```

```
0.9109562673236834
```

In [61]:
```python
print(classification_report(valid_y, knn_pred_test))
```

```
              precision    recall  f1-score   support

         0.0       0.90      0.95      0.92     14573
         1.0       0.93      0.86      0.89     11403

    accuracy                           0.91     25976
   macro avg       0.91      0.91      0.91     25976
weighted avg       0.91      0.91      0.91     25976
```

In [62]:
```python
#Linear Discriminant Analysis
ldaModel_pred_test = ldaModel.predict(valid_X)
print(accuracy_score(valid_y,ldaModel_pred_test))
ldaModel_roc = metrics.roc_curve(valid_y, ldaModel_pred_test)
ldaModel_auc = metrics.auc(ldaModel_roc[0], ldaModel_roc[1])
ldaModel_plot = metrics.RocCurveDisplay(ldaModel_roc[0], ldaModel_roc[1],
roc_auc=ldaModel_auc, estimator_name='Linear Discriminant Analysis')
```

```
0.8334231598398522
```

In [63]:
```python
print(classification_report(valid_y, ldaModel_pred_test))
```

```
              precision    recall  f1-score   support

         0.0       0.84      0.86      0.85     14573
         1.0       0.82      0.79      0.81     11403

    accuracy                           0.83     25976
   macro avg       0.83      0.83      0.83     25976
weighted avg       0.83      0.83      0.83     25976
```

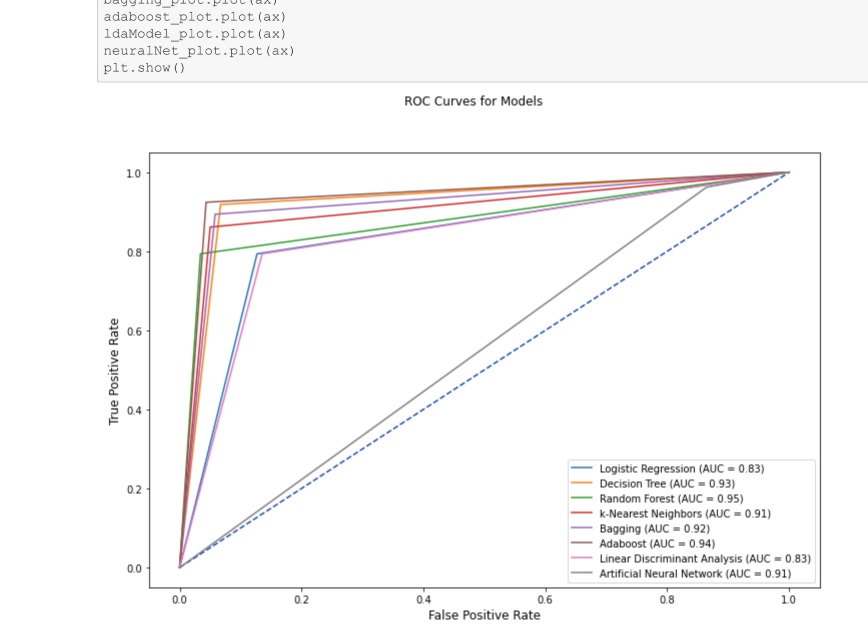
In [64]:
```python
#Neural Network
neuralNet_pred_test = neuralNet.predict(valid_X)
print(accuracy_score(valid_y,neuralNet_pred_test))
neuralNet_roc = metrics.roc_curve(valid_y, neuralNet_pred_test)
neuralNet_auc = metrics.auc(ldaModel_roc[0], neuralNet_roc[1])
neuralNet_plot = metrics.RocCurveDisplay(neuralNet_roc[0], neuralNet_roc[1],
roc_auc=neuralNet_auc, estimator_name='Artificial Neural Network')
```

```
0.4983446258084386
```

In [65]:
```python
print(classification_report(valid_y, neuralNet_pred_test))
```

```
              precision    recall  f1-score   support

         0.0       0.82      0.14      0.23     14573
         1.0       0.47      0.96      0.63     11403

    accuracy                           0.50     25976
   macro avg       0.64      0.55      0.43     25976
weighted avg       0.66      0.50      0.41     25976
```

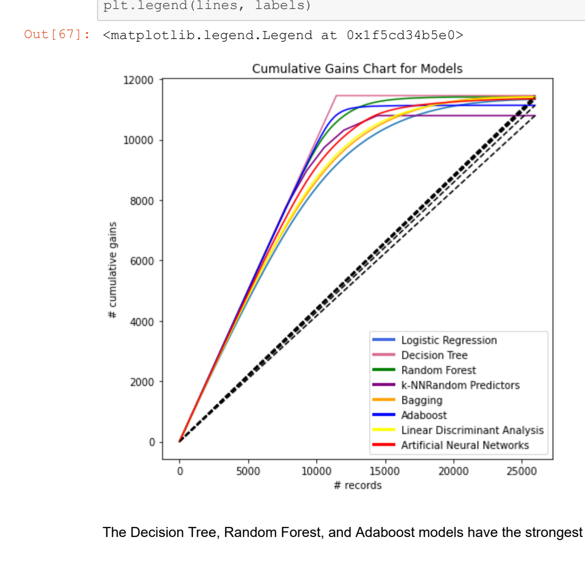
In [66]:
```python
# Plotting ROC Curves for models
fig, ax = plt.subplots(figsize=(12,8))
fig.suptitle('ROC Curves for Models', fontsize=12)
plt.plot([0, 1], [0, 1], linestyle = '--', color = '#174ab0')
plt.xlabel('',fontsize=12)
plt.ylabel('',fontsize=12)

logit_plot.plot(ax)
dtree_plot.plot(ax)
rf_plot.plot(ax)
knn_plot.plot(ax)
bagging_plot.plot(ax)
adaboost_plot.plot(ax)
ldaModel_plot.plot(ax)
neuralNet_plot.plot(ax)
plt.show()
```



The Random Forest model has the highest AUC, followed closely by Adaboost, which has strong performance when predicting true positives vs. false positives.

In [67]:
```python
from dmba import liftChart
logisticchart = pd.Series(logit.predict_proba(valid_X)[:, 1])
logisticchart = logisticchart.sort_values(ascending=False)
dtreechart = pd.Series(dtree.predict_proba(valid_X)[:, 1])
dtreechart = dtreechart.sort_values(ascending=False)
rfchart = pd.Series(rf.predict_proba(valid_X)[:, 1])
rfchart = rfchart.sort_values(ascending=False)
knnchart = pd.Series(knn.predict_proba(valid_X)[:, 1])
knnchart = knnchart.sort_values(ascending=False)
baggingchart = pd.Series(bagging.predict_proba(valid_X)[:, 1])
baggingchart = baggingchart.sort_values(ascending=False)
adaboostchart = pd.Series(adaboost.predict_proba(valid_X)[:, 1])
adaboostchart = adaboostchart.sort_values(ascending=False)
ldaModelchart = pd.Series(ldaModel.predict_proba(valid_X)[:, 1])
ldaModelchart = ldaModelchart.sort_values(ascending=False)
neuralNetchart = pd.Series(neuralNet.predict_proba(scaleInput.transform(valid_X))[:, 1])
neuralNetchart = neuralNetchart.sort_values(ascending=False)


ax= gainsChart(logisticchart, figsize=[7,7])
gainsChart(dtreechart, color='palevioletred', ax=ax)
gainsChart(rfchart, color='green', ax=ax)
gainsChart(knnchart, color='purple', ax=ax)
gainsChart(baggingchart, color='orange', ax=ax)
gainsChart(adaboostchart, color='blue', ax=ax)
gainsChart(ldaModelchart, color='yellow', ax=ax)
gainsChart(neuralNetchart, color='red', ax=ax)

ax.set_title('Cumulative Gains Chart for Models')
colors = ['royalblue', 'palevioletred', 'green', 'purple', 'orange', 'blue', 'yellow', 'red']
lines = [Line2D([0], [0], color=c, linewidth=3, linestyle='-') for c in colors]
labels=['Logistic Regression', 'Decision Tree', 'Random Forest', 'k-NN'
        'Random Predictors', 'Bagging', 'Adaboost', 'Linear Discriminant Analysis', 'Artificial Neural
 Networks']
plt.legend(lines, labels)
```

Out[67]:
```
<matplotlib.legend.Legend at 0x1f5cd34b5e0>
```



The Decision Tree, Random Forest, and Adaboost models have the strongest performance when examining cumulative gains.

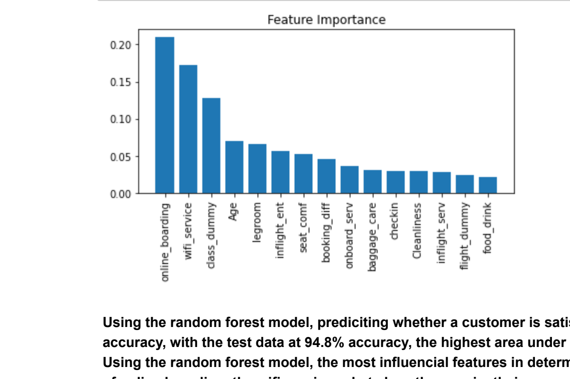
Conclusion

In [68]:
```python
# Table of metrics
metrics = [['Decision Tree', 0.926, 0.93], ['Bagging', 0.921, 0.92], ['Adaboost', 0.942, 0.94],
           ['Logistic Regression', 0.838, 0.83], ['Random Forest', 0.948, 0.95], ['k-NN', 0.911, 0.91],
           ['LDA', 0.833, 0.83], ['Neural Network', 0.498, 0.84]]
metricdf = pd.DataFrame(metrics, columns = ['Model', 'Accuracy', 'AUC'])
metricdf
```

Out[68]:

	Model	Accuracy	AUC
0	Decision Tree	0.926	0.93
1	Bagging	0.921	0.92
2	Adaboost	0.942	0.94
3	Logistic Regression	0.838	0.83
4	Random Forest	0.948	0.95
5	k-NN	0.911	0.91
6	LDA	0.833	0.83
7	Neural Network	0.498	0.84

In [81]:
```python
# Plotting importance by feature
sorted_indices = np.argsort(importance)[::-1]
plt.title('Feature Importance')
plt.bar(range(train_X.shape[1]), importance[sorted_indices], align='center')
plt.xticks(range(train_X.shape[1]), train_X.columns[sorted_indices], rotation=90)
plt.tight_layout()
plt.show()
```



Using the random forest model, prediciting whether a customer is satisfied or unsatisfied can be accomplished with high levels of accuracy, with the test data at 94.8% accuracy, the highest area under the ROC curve, and strong performance in cumulative gains. Using the random forest model, the most influencial features in determining if someone has a satisfactory experience is the quality of online boarding, the wifi service, what class they are in, their age, and the amount of legroom. Inflight entertainment and seat comfort are also important features, and are additional features airlines have a level of control over.

In [ ]: