Customer and Marketing Analytics

Raisa Nurlatifah

> note: churn data & conversion datasets filenames are changed in this work into this format:
>
> - `churn_data_yyyy_qq.csv`
> - `convert_data_yyyy_qq.csv`
>
> example:
> FROM **churn_data_q1_2020** TO **churn_data_2020_q1**

Outline

1. Business Understanding
2. Business Process
3. Create Model
4. Metrics for Simulation
5. Simulation
6. Evaluate the Simulation - Metrics
7. Evaluate the Simulation - Variable

Task 1: Business Understanding

Background and Problem Statement

Background
The aviation industry relies on customer satisfaction to stay competitive and profitable. Dissatisfied customers may lead to revenue loss. To maintain customer loyalty and attract new passengers, airlines need to understand what factors affect customer experience and take steps to improve their services.

Problem Statement
The task is to analyze customer data, uncover insights, and develop a business metrics simulation model.

Business Objectives and Metrics

Business Objectives

- To increase profitability by improving customer satisfaction through data-driven understanding

Metrics

- `Repurchase Rate` : Measure the percentage of customers who made a repeat order
- `Average Order Value` : Measure the average amount spent by customers on a certain period
- `Cost of Repurchase Customer` : Measure the cost to retain the satisfied existing customers
- `Churn Rate` : Measure the percentage of dissatisfied customers who stop using the service
- `Customer Acquisition Cost` : Measure the cost to acquire new customer

Modeling Task

Modeling Objective

Develop `an interpretable predictive model` that identifies the key factors affecting customer satisfaction and simulates its impact on revenue.

Modeling Task

- `Classify` customers as satisfied or dissatisfied based on certain features and apply them to the business metrics.
- Use `Random Forest Classier` as it can provide feature importance to help understand the satisfaction factors.

Machine Learning Metrics

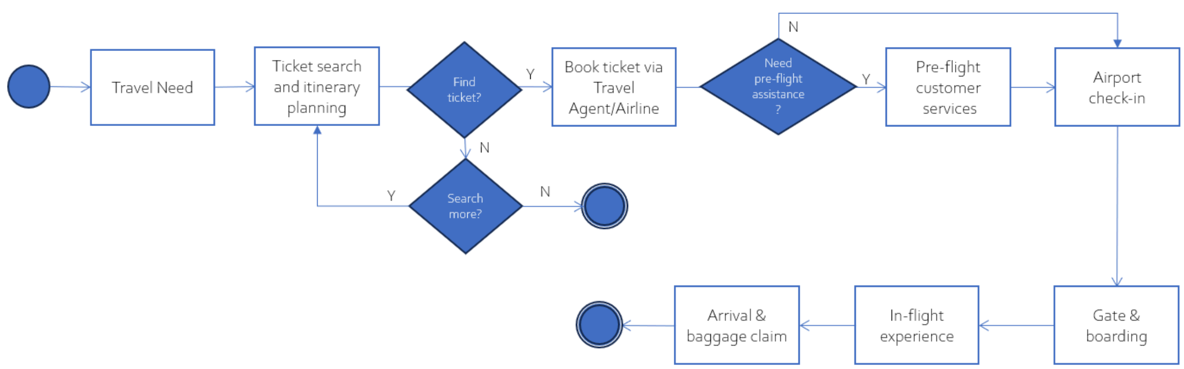
Evaluate model's performance by measuring `Accuracy, Precision, Recall, F1-Score` and `AUC-ROC values`.

Task 2: Business Process

Business Process

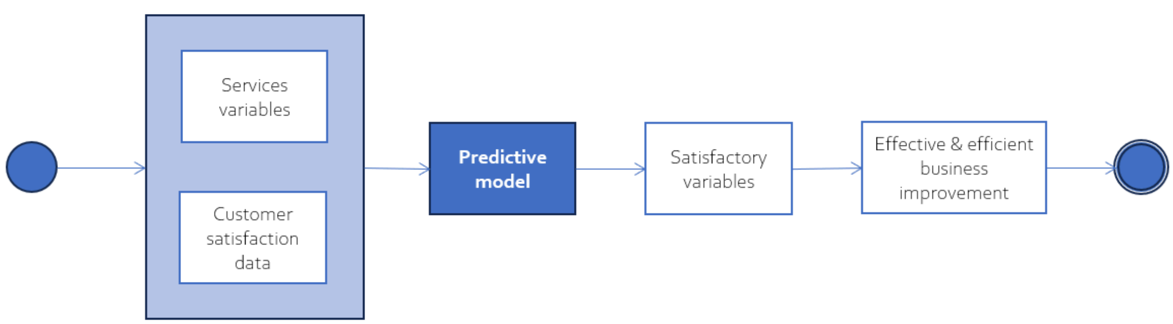
Airplane Flight Service

Existing customer flow in the aviation industry in general.



Machine learning solution

How machine learning helps the aviation.



Benefit Comparison

Before Machine Learning

The conventional customer flow, the customer experience might be less efficient due to ratherly reactive service given by the airline. Customer personalization may be limited and company might need to go through more improvement trial-and-error in any service factors as an attempt to increase customer experience which may be not effective nor efficient for company revenue growth.

The Advantage of Machine Learning
Leveraging machine learning can transforms a conventional customer flow into a data-driven personalized and efficient experience by pin pointing the key factors that influance customers overall experience which will improve customers satisfaction. By understanding the key service factors that affects customer experience, it is possible for the airline company to focus on improvement strategy that are efficient yet effective in order to maintain loyal customer, decrease customer churn and acquire new customer. Predictive analytics can help company to gain high customer satisfaction that will directly benefits the company through loss prevention and increased revenue.

Task 3: Create Model

Modeling Workflow

1. Data validation
Importing data and data validation

2. Exploratory Data Analysis
Descriptive Analysis, Univariate Analysis, and Correlation Analysis

3. Data Pre-processing
Missing value handling, feature engineering, and normalization/standardization

4. Feature Importanace Modeling
Model fitting and evaluation

5. Rule-based Modeling
Rule-based model definition

Data Validation

Data Description

Input Variable:

- `id` : customer unique identifier, numeric.
- `Gender` : customers' gender, nominal (male, female).
- `Customer Type` : customers loyalty class, nominal (loyal, disloyal).
- `Age` : customers' age, numeric
- `Type of Travel` : customers travel purpose class, nominal (personal, business)
- `Class` : customers booked flight class, nominal (eco plus, businesss, eco)
- `Flight Distance` : the distance of a flight, numeric
- `Inflight wifi service` : customers rating on inflight wifi service, ordinal (0 to 5)
- `Departure/Arrival time convenient` : customers rating on convenience of departure/arrival time, ordinal (0 to 5)
- `Ease of Online booking` : customers rating on ease of online booking, ordinal (0 to 5)
- `Gate location` : customers rating on gate location, ordinal (0 to 5)
- `Food and drink` : customers rating on food and drink, ordinal (0 to 5)
- `Online boarding` : customers rating on online boarding, ordinal (0 to 5)
- `Seat comfort` : customers rating on seat comfort, ordinal (0 to 5)
- `Inflight entertainment` : customers rating on inflight entertainment, ordinal (0 to 5)

- `On-board service` : customers rating on on-board service, ordinal (0 to 5)
- `Leg room service` : customers rating on leg room service, ordinal (0 to 5)
- `Baggage handling` : customers rating on baggage handling, ordinal (0 to 5)
- `Checkin service` : customers rating on check-in service, ordinal (0 to 5)
- `Inflight service` : customers rating on inflight service, ordinal (0 to 5)
- `Cleanliness` : customers rating on cleanliness, ordinal (0 to 5)
- `Departure Delay in Minutes` : number minutes that a flight is delayed past its scheduled departure time, numeric.
- `Arrival Delay in Minutes` : number of minutes that a flight is delayed past its scheduled arrival time, numeric.

Target Feature

- `satisfaction` : customer satisfaction class, nominal (satisfied, dissatisfied)

Load Data

Load Machine Learning packages

In [28]:
```
# Load data manipulation package
import numpy as np
import pandas as pd

# Load data visualization package
import matplotlib.pyplot as plt
import seaborn as sns
```

Import training data

In [30]:
```
# Create a read dataset function
def read_data(path):
    """
    Reads a CSV file, removes duplicates, and returns a DataFrame.

    Parameters
    ----------
    path : str
        Path to the CSV file.

    Returns
    -------
    pandas.DataFrame
        DataFrame without duplicates.
    """

    # 1. Read data
    data = pd.read_csv(path,
                       index_col = 0,
                       low_memory = False) # Disable automatic type inference for memory efficiency

    # 2. Drop duplicates
    data = data.drop_duplicates()

    # 3. print data shape
    print('Data shape :', data.shape)

    return data
```

In [31]:
```
# Read data
satisfaction_data = read_data(path = 'satisfaction_df.csv')
```

```
Data shape : (103594, 25)
```

In [32]:
```
#Check data
satisfaction_data.head()
```

Out[32]:

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

5 rows × 25 columns

Validate Data

The `Unnamed:0` column is redundant with the index and will have no further use hence will be deleted.

In [35]:
```
#Drop unnecessary column
satisfaction_data.drop(columns=['Unnamed: 0'], inplace=True)
```

In [36]:
```
#Check if ID is unique
print(f'Number of unique customer: {satisfaction_data.id.nunique()}')
```

```
Number of unique customer: 103594
```

Set `id` as Index

- Since every customer is unique
- We can set the `id` as data index
- We can use the `id` as index to keep tracking the predicted outcome according to the index

In [38]:
```
# set customerID as index
satisfaction_data.set_index('id', inplace=True)
```

In [39]:
```
# check the result
satisfaction_data.head()
```

Out[39]:

id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	...	e
70172	Male	Loyal Customer	13	Personal Travel	Eco Plus	460	3	4	3	1	...	
5047	Male	disloyal Customer	25	Business travel	Business	235	3	2	3	3	...	
110028	Female	Loyal Customer	26	Business travel	Business	1142	2	2	2	2	...	
24026	Female	Loyal Customer	25	Business travel	Business	562	2	5	5	5	...	
119299	Male	Loyal Customer	61	Business travel	Business	214	3	3	3	3	...	

5 rows × 23 columns

In [40]:

```
# check data duplicate
satisfaction_data.duplicated().sum()
```

Out[40]: 0

In [41]:

```
#Check missing value
satisfaction_data.isna().sum()
```

Out[41]:

```
Gender                               0
Customer Type                        0
Age                                  0
Type of Travel                       0
Class                                0
Flight Distance                      0
Inflight wifi service                0
Departure/Arrival time convenient    0
Ease of Online booking               0
Gate location                        0
Food and drink                       0
Online boarding                      0
Seat comfort                         0
Inflight entertainment               0
On-board service                     0
Leg room service                     0
Baggage handling                     0
Checkin service                      0
Inflight service                     0
Cleanliness                          0
Departure Delay in Minutes           0
Arrival Delay in Minutes             0
satisfaction                         0
dtype: int64
```

In [42]:

```
#Check data type
satisfaction_data.dtypes
```

```
Out[42]: Gender                                object
         Customer Type                         object
         Age                                    int64
         Type of Travel                        object
         Class                                 object
         Flight Distance                        int64
         Inflight wifi service                  int64
         Departure/Arrival time convenient      int64
         Ease of Online booking                 int64
         Gate location                          int64
         Food and drink                         int64
         Online boarding                        int64
         Seat comfort                           int64
         Inflight entertainment                 int64
         On-board service                       int64
         Leg room service                       int64
         Baggage handling                       int64
         Checkin service                        int64
         Inflight service                       int64
         Cleanliness                            int64
         Departure Delay in Minutes             int64
         Arrival Delay in Minutes             float64
         satisfaction                          object
         dtype: object
```

Data Validation Summary

- No duplicated values to handle
- No missing values in the next preprocessing stage
- Encode categorical features
- No need for Train-Test data splitting since test dataset are provided separatedly.

Data Splitting

- `Satisfaction_df.csv` provides 103594 data for training purpose only.
- Test set data will be provided on `test.csv`
- The training data will be split into X and y only

Split Data

```
In [47]: # Create a split input and output function
def split_input_output(data, target_column):
    """
    Splits a DataFrame into input (X) and output (y).

    Parameters
    ----------
    data : pandas.DataFrame
        Input DataFrame.

    target_column : str
        Name of the target column.

    Returns
    -------
    X : pandas.DataFrame
        DataFrame containing feature columns.

    y : pandas.Series
        Series containing the target variable.
    """

    X = data.drop(columns = target_column)
    y = data[target_column]
```

```
    return X, y
```

In [48]:
```
# Split input and output
X, y = split_input_output(data = satisfaction_data,
                          target_column = "satisfaction")
```

In [49]:
```
# Check data dimension
n_samples, n_features = X.shape

# Print number of samples and features
print(f'Number of samples  :    {n_samples}')
print(f'Number of features :    {n_features}')
```

```
Number of samples  :    103594
Number of features :    22
```

In [50]:
```
# Count y value
y.value_counts()
```

Out[50]:
```
satisfaction
Dissatisfied    58697
Satisfied       44897
Name: count, dtype: int64
```

Data Splitting Summary

- The training and validation set data are splitted into 0.7 : 0.3 ratio
- Only training set data will be use in EDA and modeling stages

Explanatory Data Analysis

In [53]:
```
# create EDA dataset
eda_df = pd.concat([X, y], axis=1)
```

In [54]:
```
# check the result
eda_df.head()
```

Out[54]:

id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	...	e
70172	Male	Loyal Customer	13	Personal Travel	Eco Plus	460	3	4	3	1	...	
5047	Male	disloyal Customer	25	Business travel	Business	235	3	2	3	3	...	
110028	Female	Loyal Customer	26	Business travel	Business	1142	2	2	2	2	...	
24026	Female	Loyal Customer	25	Business travel	Business	562	2	5	5	5	...	
119299	Male	Loyal Customer	61	Business travel	Business	214	3	3	3	3	...	

5 rows × 23 columns

Descriptive Analysis

In [56]:
```
# Describe
eda_df.describe()
```

Out[56]:

	Age	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	Food and drink
count	103594.000000	103594.000000	103594.000000	103594.000000	103594.000000	103594.000000	103594.000000
mean	39.380466	1189.325202	2.729753	3.060081	2.756984	2.977026	3.202126
std	15.113125	997.297235	1.327866	1.525233	1.398934	1.277723	1.32940
min	7.000000	31.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	27.000000	414.000000	2.000000	2.000000	2.000000	2.000000	2.000000
50%	40.000000	842.000000	3.000000	3.000000	3.000000	3.000000	3.000000
75%	51.000000	1743.000000	4.000000	4.000000	4.000000	4.000000	4.000000
max	85.000000	4983.000000	5.000000	5.000000	5.000000	5.000000	5.000000

There might be outliers in `Flight Distance`, `Departure Delay in Minutes`, and `Arrival Delay in Minutes`

Differentiate Categorical and Numerical data

- Split between categorical and numerical values.
- Ordinal is treated as categorical even though it is presented in a numerical format as it serves qualitative data with has mathematical meaning.

Numerical data:

- `Age`
- `Flight Distance`
- `Departure Delay in Minutes`
- `Arrival Delay in Minutes`

The rest of the column are categorical

Numerical Data Analysis

In [60]:

```
# Create a get numerical function
def get_numerical_features(data, numerical_column):
    """
    Extracts numerical features from a DataFrame based on a given list of column names.

    Parameters
    ----------
    data : pandas.DataFrame
        Input DataFrame containing various features.

    numerical_column : list of str
        List of column names representing numerical features.

    Returns
    -------
    pandas.DataFrame
        DataFrame containing only the specified numerical columns.
    """

    numerical_data = data[numerical_column]

    return numerical_data
```

In [61]:
```
# Set numerical column
numerical_columns = [
        "Age",
        "Flight Distance",
        "Departure Delay in Minutes",
        "Arrival Delay in Minutes"]

# Differentiate numerical dataframe
num_cols = get_numerical_features(data = eda_df,
                                  numerical_column = numerical_columns)


# Check numerical data
num_cols.head()
```

Out[61]:

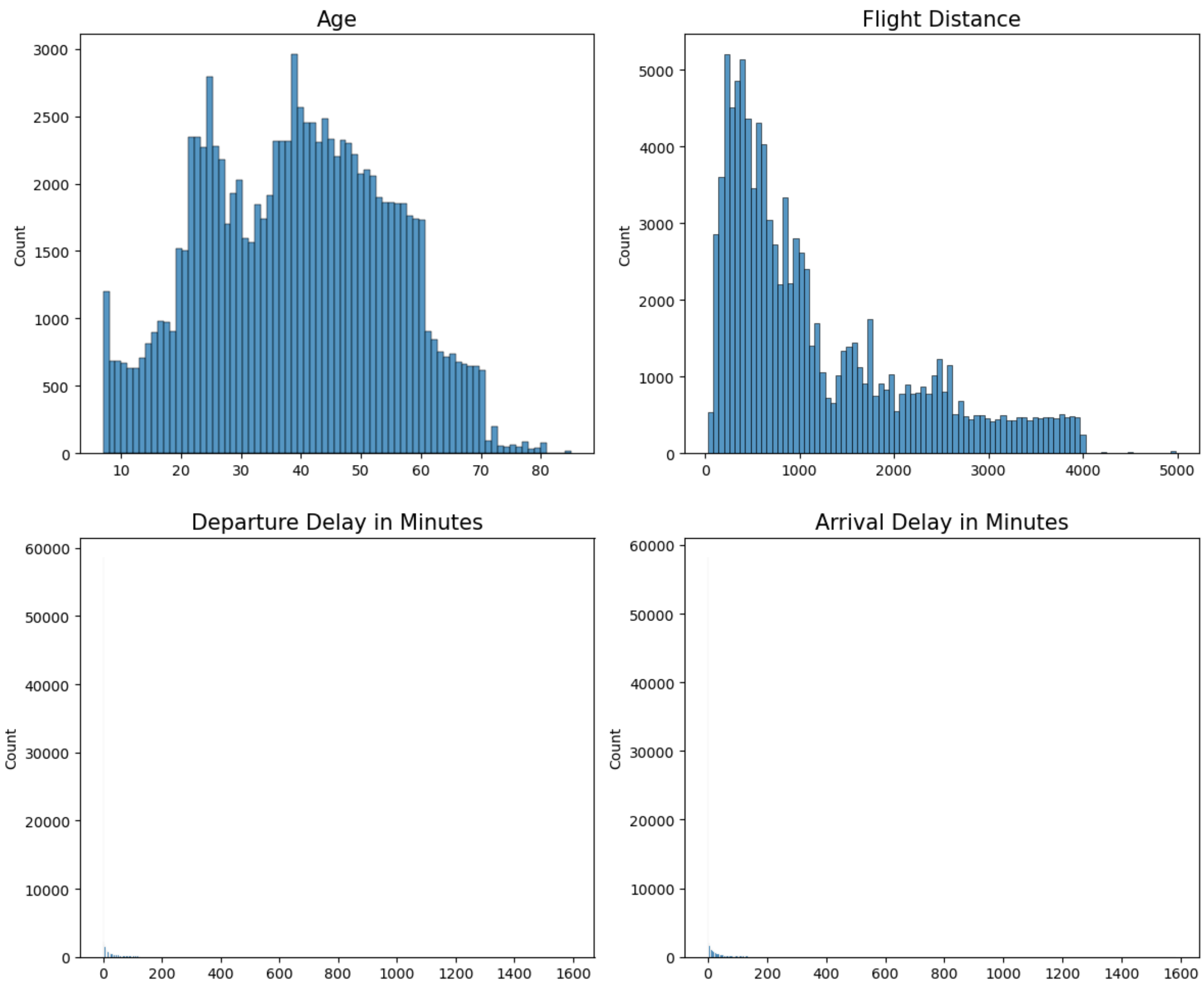
id	Age	Flight Distance	Departure Delay in Minutes	Arrival Delay in Minutes
70172	13	460	25	18.0
5047	25	235	1	6.0
110028	26	1142	0	0.0
24026	25	562	11	9.0
119299	61	214	0	0.0

In [62]:
```
# check numerical columns
print(f'Numerical features : \n{list(num_cols)}')
```

```
Numerical features :
['Age', 'Flight Distance', 'Departure Delay in Minutes', 'Arrival Delay in Minutes']
```

In [63]:
```
# List numerical column
num = list(num_cols.columns)
```

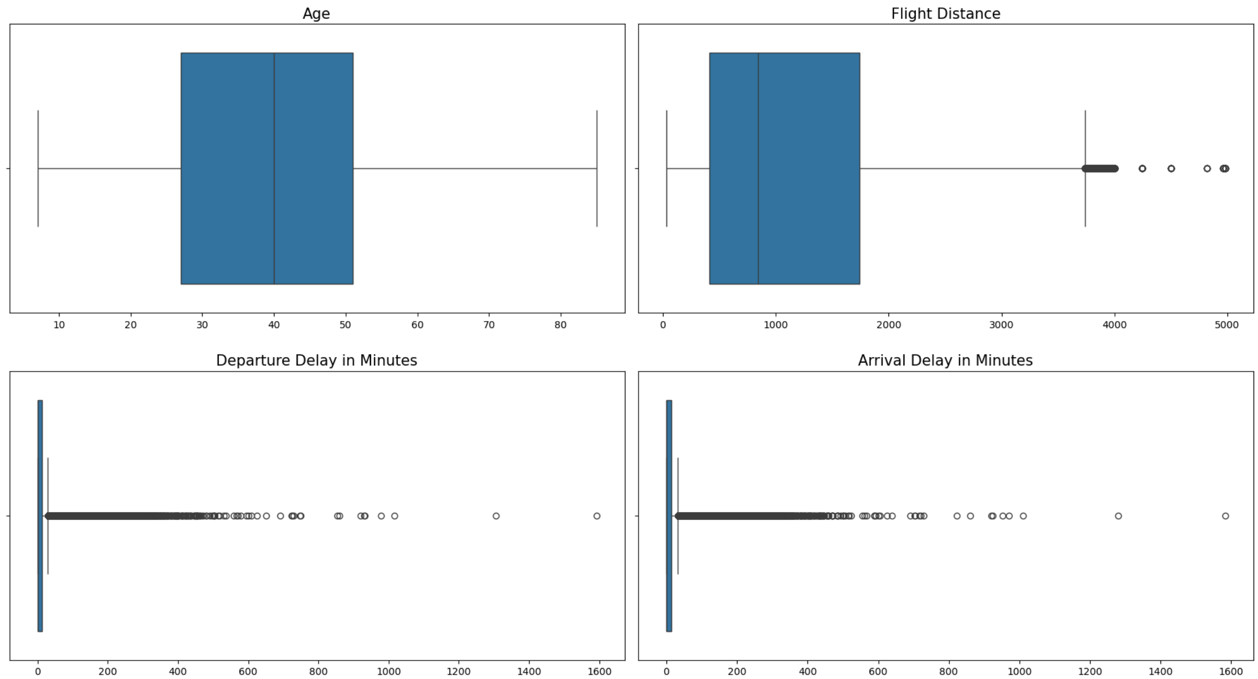
In [64]:
```
# Create histplot
plt.figure(figsize=(12,10))
for i in range(0, len(num)):
    plt.subplot(2,2,i+1)
    sns.histplot(x=eda_df[num[i]])
    plt.title(num[i], fontsize=15)
    plt.xlabel(' ')
    plt.tight_layout()
```



Above graph shows:

- `Age` is somewhat has a normal distribution
- `Flight Distance` has skewed distribution and might have slight outliers
- There are huge potential outliers in `Departure Delay in Minutes` and `Arrival Delay in Minutes`

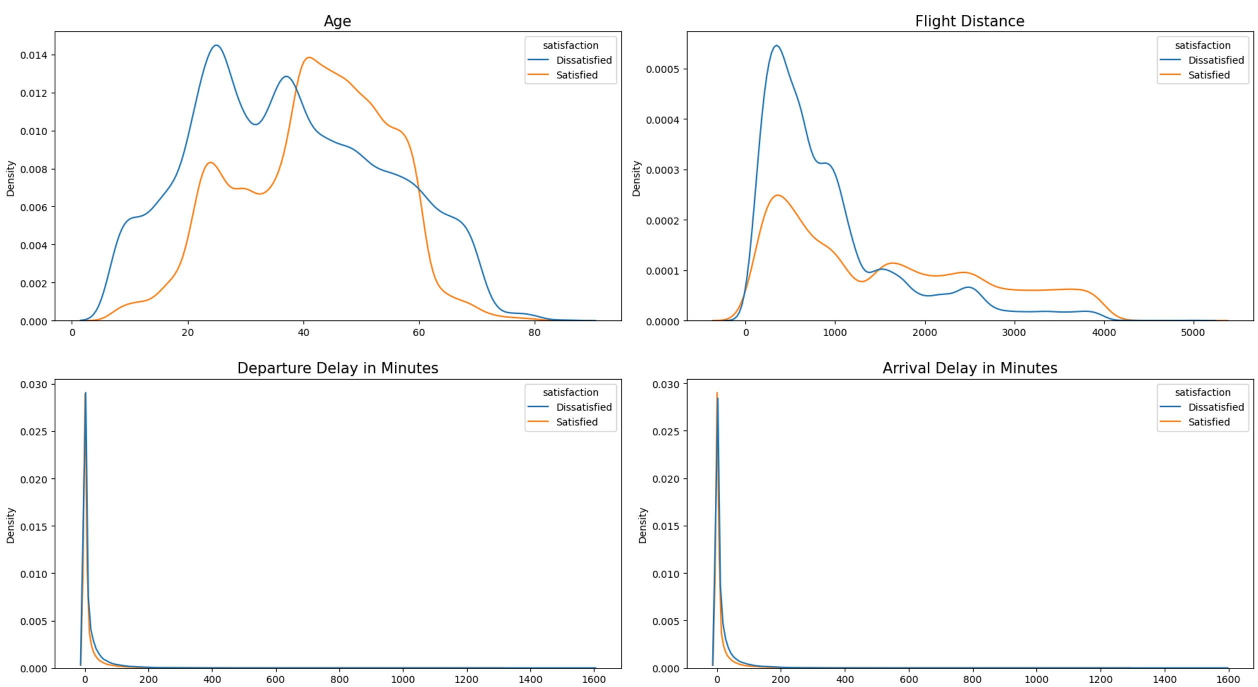
In [66]:
```
# Create boxplot
plt.figure(figsize=(18,10))
for i in range(0, len(num)):
    plt.subplot(2,2,i+1)
    sns.boxplot(x=eda_df[num[i]])
    plt.title(num[i], fontsize=15)
    plt.xlabel(' ')
    plt.tight_layout()
```



Above graph confirms that:

- No outlier in `Age`
- `Flight Distance` has outliers
- There are huge numbe of outliers in `Departure Delay in Minutes` and `Arrival Delay in Minutes`

In [68]:
```python
# Create kde plot
plt.figure(figsize=(18,10))
for i in range(0, len(num)):
    plt.subplot(2,2,i+1)
    sns.kdeplot(x=eda_df[num[i]], hue=eda_df['satisfaction'])
    plt.title(num[i], fontsize=15)
    plt.xlabel(' ')
    plt.tight_layout()
```



Categorical Data Analysis

In [70]:
```
# Create function to get categorical column list function
def get_categorical_columns(data, y_column, numerical_column):
    """
    Identifies categorical columns by excluding numerical columns and target column(s).

    Parameters
    ----------
    data : pandas.DataFrame
        Input DataFrame containing various features.

    y_column : str or list of str
        Target column(s) to exclude from categorical features.

    numerical_column : list of str
        List of column names representing numerical features.

    Returns
    -------
    list of str
        List of categorical column names.
    """

    X_column = set(data.columns).difference(set(y_column))

    categorical_columns = X_column.difference(set(numerical_columns))
    cat_list = list(categorical_columns)

    return cat_list

# Create function to get categorical dataframe
def extract_categorical_data(data, categorical_column):
    """
    Selects categorical columns from a DataFrame based on a given list of column names.

    Parameters
    ----------
    data : pandas.DataFrame
        Input DataFrame containing various features.

    categorical_column : list of str
        List of column names representing categorical features.

    Returns
    -------
    pandas.DataFrame
        DataFrame containing only the specified categorical columns.
    """

    categorical_data = data[categorical_column]

    return categorical_data
```

In [71]:
```
# Set target variable to drop
y_column = ['satisfaction']

# Get categorical column names
categorical_columns = get_categorical_columns(data = eda_df,
                                              y_column = y_column,
                                              numerical_column = numerical_columns
                                              )

# Extract categorical data
cat_cols = extract_categorical_data(data = eda_df,
                                    categorical_column = categorical_columns)
```

```
# Display first few rows of categorical data
cat_cols.head()
```

Out[71]:

	Gate location	Checkin service	Leg room service	On-board service	Food and drink	Type of Travel	Customer Type	Class	Inflight wifi service	Ease of Online booking	Baggage handling	S comf
id												
70172	1	4	3	4	5	Personal Travel	Loyal Customer	Eco Plus	3	3	4	
5047	3	1	5	1	1	Business travel	disloyal Customer	Business	3	3	3	
110028	2	4	3	4	5	Business travel	Loyal Customer	Business	2	2	4	
24026	5	1	5	2	2	Business travel	Loyal Customer	Business	2	5	3	
119299	3	3	4	3	4	Business travel	Loyal Customer	Business	3	3	4	

In [72]:

```
# check categorical columns
print(f'Categorical features : \n{list(cat_cols)}')
```

```
Categorical features :
['Gate location', 'Checkin service', 'Leg room service', 'On-board service', 'Food and drink', 'Type of Tr
avel', 'Customer Type', 'Class', 'Inflight wifi service', 'Ease of Online booking', 'Baggage handling', 'S
eat comfort', 'Gender', 'Cleanliness', 'Online boarding', 'Departure/Arrival time convenient', 'Inflight s
ervice', 'Inflight entertainment']
```

In [73]:

```
# List categorical column
cat = list(cat_cols.columns)

print(f'Number Categorical features : {len(cat)}')
```

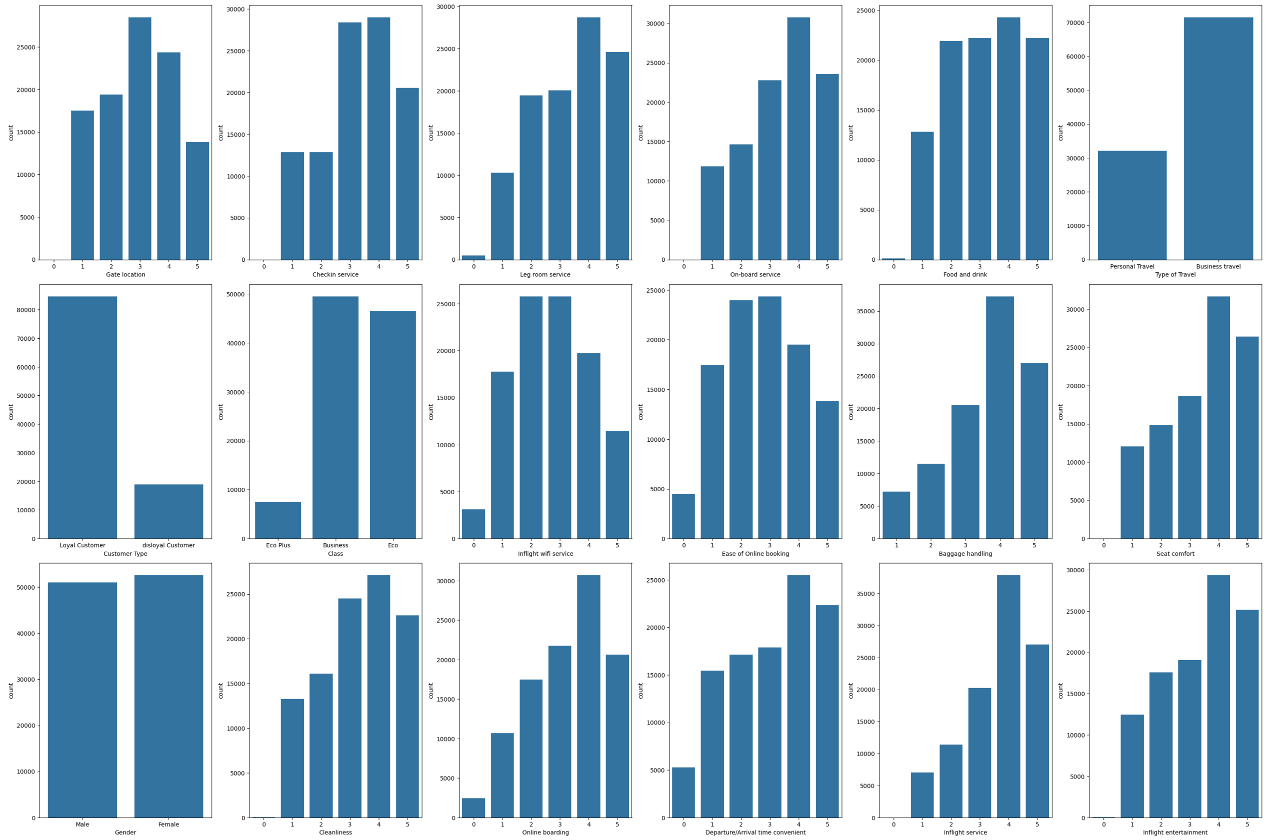
```
Number Categorical features : 18
```

In [74]:

```
# Create countplot for categorical features
fig, axes = plt.subplots(3, 6, figsize=(30, 20))

# Calculate row and column indices for each subplot
for i, col in enumerate(cat):
    row = i //  6   # Integer division to get row index
    col_idx = i % 6 # Modulo to get column index
    sns.countplot(x=col, data=cat_cols, ax=axes[row, col_idx])
    axes[row, col_idx].set_xlabel(col)

plt.tight_layout()
```



Explanatory Data Analysis Summary

Almost all of the numerical features are not clearly separable by the target feature, which suggests that these features do not contain enough information to effectively predict or classify the target variable. Hence the pre-processing will only be applied to categorical data only.

Pre-processing Data

Encode Nominal Categorical Data

In [79]:
```
from sklearn.preprocessing import OneHotEncoder

# Create categorical encoding (OHE) function
def encoding_cat_feature(data, fit=False, encoder=None):
    """
    Encodes categorical features using one-hot encoding.

    Parameters
    ----------
    data : pandas.DataFrame
        DataFrame containing categorical features to be encoded.

    fit : bool, default=False
        If True, fits a new OneHotEncoder to the data. Otherwise, uses the provided encoder.

    encoder : OneHotEncoder, optional
        Pre-trained OneHotEncoder to use for encoding. Ignored if `fit=True`.

    Returns
    -------
    encoder : OneHotEncoder
        The OneHotEncoder object used for transformation.

    final_df : pandas.DataFrame
        DataFrame with categorical features replaced by their one-hot encoded values.
```

```
    """

    # Get copy and reset_index
    data_copy = data.copy().reset_index(drop=True)

    # Extract the target column
    target_col = data_copy['satisfaction']

    # Drop the target column from the features
    data_copy = data_copy.drop('satisfaction', axis=1)

    # Select categorical features
    cat_features = data_copy.select_dtypes(include='object').columns

    # If fitting the encoder, ensure it knows all categories
    if fit:
        ohe = OneHotEncoder(handle_unknown='ignore', drop='first', sparse_output=False)

        # Fit and transform on categorical columns
        ohe.fit(data_copy[cat_features])
        encoder = ohe
        encoded_df = pd.DataFrame(ohe.transform(data_copy[cat_features]))
    else:
        # Use existing encoder to transform
        encoded_df = pd.DataFrame(encoder.transform(data_copy[cat_features]))

    # Rename columns based on the encoder output
    encoded_df.columns = encoder.get_feature_names_out(cat_features)

    # Drop the original categorical columns
    dropped_data = data_copy.drop(cat_features, axis=1)
    final_df = pd.concat([dropped_data, encoded_df], axis=1)

    return encoder, final_df
```

In [80]:
```
# Define Training Dataset
train_set = pd.concat([X, y], axis=1)

# Encode categorical data
encoder, X_encoded = encoding_cat_feature(data = train_set,
                                          fit = True)

# show train_set (sanity check)
X_encoded.head()
```

Out[80]:

	Age	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	Food and drink	Online boarding	Seat comfort	Inflight entertainment	...	Che se
0	13	460	3	4	3	1	5	3	5	5	...	
1	25	235	3	2	3	3	1	3	1	1	...	
2	26	1142	2	2	2	2	5	5	5	5	...	
3	25	562	2	5	5	5	2	2	2	2	...	
4	61	214	3	3	3	3	4	5	5	3	...	

5 rows × 23 columns

In [81]:
```
encoder.categories_
```

Out[81]:
```
[array(['Female', 'Male'], dtype=object),
 array(['Loyal Customer', 'disloyal Customer'], dtype=object),
 array(['Business travel', 'Personal Travel'], dtype=object),
 array(['Business', 'Eco', 'Eco Plus'], dtype=object)]
```

Modeling

Feature Selection

Before modeling it is important to convert the target data into numerical value.

- `Satisfed` = 1
- `Dissatisfed` = 0

In [85]:
```python
from sklearn.preprocessing import LabelEncoder

# Create encoder for target column function
def encode_labels(y_data):
    """
    Encodes the target variable using LabelEncoder.

    Parameters
    ----------
    y_data : array-like
        Target variable containing categorical labels.

    Returns
    -------
    label_encoder : LabelEncoder
        Fitted LabelEncoder instance.

    y_encoded : numpy.ndarray
        Encoded labels as numerical values.
    """

    label_encoder = LabelEncoder()
    y_encoded = label_encoder.fit_transform(y_data)

    return label_encoder, y_encoded
```

In [86]:
```python
#Encode y train data
label_encoder, y_train_encoded = encode_labels(y)
```

In [87]:
```python
print(label_encoder.classes_)
```

```
['Dissatisfied' 'Satisfied']
```

Assessing feature importance to select 5 features that is strongly relevant to target data using `RandomForestClassifier`, by selecting five highest scores.

In [89]:
```python
from sklearn.ensemble import RandomForestClassifier

# Initialize and train the model
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_encoded, y_train_encoded)

# Get feature importances
feature_importances = rf_model.feature_importances_

# Display feature importances
feature_names = X_encoded.columns
importance_df = pd.DataFrame({'Feature': feature_names, 'Importance': feature_importances})
importance_df = importance_df.sort_values(by='Importance', ascending=False)

importance_df
```

Out[89]:

	Feature	Importance
7	Online boarding	0.168829
2	Inflight wifi service	0.149961
20	Type of Travel_Personal Travel	0.105048
21	Class_Eco	0.074040
9	Inflight entertainment	0.055648
8	Seat comfort	0.047139
1	Flight Distance	0.041115
11	Leg room service	0.039089
4	Ease of Online booking	0.037418
19	Customer Type_disloyal Customer	0.036786
10	On-board service	0.033339
0	Age	0.031757
12	Baggage handling	0.027631
15	Cleanliness	0.025531
13	Checkin service	0.023712
14	Inflight service	0.022059
3	Departure/Arrival time convenient	0.017566
5	Gate location	0.015957
6	Food and drink	0.012794
17	Arrival Delay in Minutes	0.012369
16	Departure Delay in Minutes	0.011323
22	Class_Eco Plus	0.006389
18	Gender_Male	0.004499

Based on above features selection, the five features that will be used in the rule-based modeling are:

- `Online boarding`
- `Inflight wifi service`
- `Type of Travel_Personal Travel`
- `Class_Eco`
- `Inflight entertainment`

Rule-Based Model

Rule-based Classification Logic

1. For ordinal values (0 to 5):
    - `Online boarding`
    - `Inflight wifi service`
    - `Inflight entertainment`

If the rating is 3 or above, the customer is considered satisfied with the service; otherwise, dissatisfied.

2. `Type of Travel` (Personal Travel encoded 1 and 0): 1 (Personal Travel) indicates travel purposes, while 0 represents business travel.

3. `Class` (Eco encoded 1 and 0): If 1 (Eco class), the customer may be less satisfied due to more basic service, and 0 represents a higher class with better facilities.

4. If three or more features are satisfied, customer is considered satisfied

In [94]:
```python
# Create a function that classify the rule based model
def classify_satisfaction_rule_based(row):
    """
    Classifies customer satisfaction based on predefined feature rules.

    Parameters
    ----------
    row : pandas.Series
        A row from the DataFrame containing relevant features for classification.

    Returns
    -------
    str
        Satisfaction label, either 'Satisfied' or 'Dissatisfied'.
    """

    # Rule 1: Online boarding (ordinal 0 to 5)
    if row['Online boarding'] >= 3:
        online_boarding_satisfaction = True
    else:
        online_boarding_satisfaction = False

    # Rule 2: Inflight wifi service (ordinal 0 to 5)
    if row['Inflight wifi service'] >= 3:
        inflight_wifi_satisfaction = True
    else:
        inflight_wifi_satisfaction = False

    # Rule 3: Type of Travel (1 = Personal Travel, 0 = other)
    if row['Type of Travel_Personal Travel'] == 1:
        personal_travel_satisfaction = True
    else:
        personal_travel_satisfaction = False

    # Rule 4: Class (1 = Eco, 0 = other)
    if row['Class_Eco'] == 1:
        eco_class_satisfaction = False  # Lower class might indicate dissatisfaction
    else:
        eco_class_satisfaction = True  # Higher class might indicate satisfaction

    # Rule 5: Inflight entertainment (ordinal 0 to 5)
    if row['Inflight entertainment'] >= 3:
        inflight_entertainment_satisfaction = True
    else:
        inflight_entertainment_satisfaction = False

    # Combine the rules: If most of the features are satisfied (True), classify as 'Satisfied'
    satisfied_count = sum([online_boarding_satisfaction, inflight_wifi_satisfaction,
                           personal_travel_satisfaction, eco_class_satisfaction,
                           inflight_entertainment_satisfaction])

    if satisfied_count >= 3:  # If 3 or more features indicate satisfaction
        return 'Satisfied'
    else:
        return 'Dissatisfied'
```

In [95]:
```
# Copy X to avoid modifying the original data
X_ruled = X_encoded.copy()

# Apply the rule-based classification function
X_ruled['satisfaction'] = X_ruled.apply(classify_satisfaction_rule_based, axis=1)

# Show applied rule
X_ruled_features = X_ruled[['Online boarding', 'Inflight wifi service',
                    'Type of Travel_Personal Travel', 'Class_Eco',
                    'Inflight entertainment', 'satisfaction']]

X_ruled_features.head()
```

Out[95]:

	Online boarding	Inflight wifi service	Type of Travel_Personal Travel	Class_Eco	Inflight entertainment	satisfaction
0	3	3	1.0	0.0	5	Satisfied
1	3	3	0.0	0.0	1	Satisfied
2	5	2	0.0	0.0	5	Satisfied
3	2	2	0.0	0.0	2	Dissatisfied
4	5	3	0.0	0.0	3	Satisfied

Task 4: Build Metrics for Simulation

Satisfied Class Data

The datasets provide all the features that are available in Task 1 with additional column `Conversion` in year 2020 and 2021. This data rerspresents only `satisfied` customer which will be used on `Repurchase Rate` and `Average Order Value` business metrics.

Import Data

In [100…
```
satisfied_1 = read_data(path = 'convert_data_2020_q1.csv')
satisfied_2 = read_data(path = 'convert_data_2020_q2.csv')
satisfied_3 = read_data(path = 'convert_data_2020_q3.csv')
satisfied_4 = read_data(path = 'convert_data_2020_q4.csv')

satisfied_5 = read_data(path = 'convert_data_2021_q1.csv')
satisfied_6 = read_data(path = 'convert_data_2021_q2.csv')
satisfied_7 = read_data(path = 'convert_data_2021_q3.csv')
satisfied_8 = read_data(path = 'convert_data_2021_q4.csv')
```

```
Data shape : (6949, 25)
Data shape : (8859, 25)
Data shape : (7653, 25)
Data shape : (10621, 25)
Data shape : (10245, 25)
Data shape : (9776, 25)
Data shape : (14819, 25)
Data shape : (9688, 25)
```

In [101…
```
# Concat yearly data
satisfied_2020 = pd.concat([satisfied_1,satisfied_2 ,satisfied_3 ,satisfied_4], ignore_index=True)
satisfied_2021 = pd.concat([satisfied_5 ,satisfied_6 ,satisfied_7 ,satisfied_8], ignore_index=True)

# Concat all data
satisfied_all = pd.concat([satisfied_2020,satisfied_2021], ignore_index=True)
```

In [102…
```
# Display satisfied data 2020
print(f'Satisfied 2020 data shape: {satisfied_2020.shape}')
```

```
satisfied_2020.head()
```

```
Satisfied 2020 data shape: (34082, 25)
```

Out[102…

	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	...	On-board service
0	185933	Male	Loyal Customer	54	Business travel	Business	3758	5	5	5	...	4
1	127711	Female	disloyal Customer	20	Business travel	Eco	641	5	0	5	...	5
2	173115	Female	disloyal Customer	50	Business travel	Business	1127	4	4	4	...	5
3	92061	Female	Loyal Customer	36	Business travel	Business	1765	2	2	2	...	5
4	143699	Female	Loyal Customer	39	Business travel	Business	3145	3	3	3	...	4

5 rows × 25 columns

In [103…

```
#Check if ID is unique
print(f'Number of unique customer: {satisfied_2020['id'].nunique()}')
```

```
Number of unique customer: 31217
```

In [104…

```
# Display satisfied data 2021
print(f'Satisfied 2021 data shape: {satisfied_2021.shape}')
satisfied_2021.head()
```

```
Satisfied 2021 data shape: (44528, 25)
```

Out[104…

	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	...	On-board service
0	115972	Female	Loyal Customer	16	Business travel	Eco	491	4	5	5	...	3
1	54759	Male	Loyal Customer	40	Business travel	Business	3578	5	5	5	...	4
2	131413	Female	Loyal Customer	26	Business travel	Business	3493	3	3	3	...	5
3	20307	Male	Loyal Customer	34	Business travel	Business	762	1	1	1	...	4
4	135259	Female	Loyal Customer	40	Business travel	Business	575	5	5	5	...	4

5 rows × 25 columns

In [105…

```
#Check if ID is unique
print(f'Number of unique customer: {satisfied_2021['id'].nunique()}')
```

```
Number of unique customer: 39719
```

In [106…

```
#Check if ID is unique
print(f'Number of unique customer: {satisfied_all['id'].nunique()}')
```

```
Number of unique customer: 65565
```

Business Metrics Assumption

Repurchase Rate

To calculate `Repurchase rate`, Number of Unique Customer will be used to determine how many percentage the satisfied customers are making another purchase within the time period.

calculate the `Average Purchases per Customer` using the formula:

$$\text{Average Purchases per Customer} = \frac{\text{Total Rows}}{\text{Unique Customers}}$$

To estimate the `Repurchase Rate`, the formula are follow:

$$\text{Repurchase Rate Estimate} = \frac{\text{Average Purchases per Customer} - 1}{\text{Average Purchases per Customer}} \times 100\%$$

In [110…

```
# Create a function to calculate repurchase rate
def get_repurchase_rate(data):
    """
    Calculates total purchases, unique customers, average purchases per customer,
    and estimated repurchase rate.

    Parameters
    ----------
    data : pandas.DataFrame
        DataFrame containing purchase data.

    Returns
    -------
    dict
        Dictionary with the following metrics:
        - 'total_purchases': Total number of purchases.
        - 'unique_customers': Number of unique customers.
        - 'avg_purchases_per_customer': Average purchases per customer.
        - 'repurchase_rate': Estimated percentage of customers who made multiple purchases.
    """

    total_purchases = len(data)

    unique_customers = data['id'].nunique()

    avg_purchases_per_customer = total_purchases / unique_customers if unique_customers > 0 else 0

    repurchase_rate = ((avg_purchases_per_customer - 1) / avg_purchases_per_customer) * 100 if avg_purcha
    repurchase_rate = round(repurchase_rate, 2)

    return {
        "Total Purchases": total_purchases,
        "Unique Customers": unique_customers,
        "Avg Purchases per Customer (%)": round(avg_purchases_per_customer, 2),
        "Repurchase Rate (%)": repurchase_rate
    }
```

In [111…

```
# Display repurchase rate 2020
repurchase_rate_2020 = get_repurchase_rate(satisfied_2020)
print('Repurchase Rate 2020:')
repurchase_rate_2020
```

```
Repurchase Rate 2020:
```

Out[111…

```
{'Total Purchases': 34082,
 'Unique Customers': 31217,
 'Avg Purchases per Customer (%)': 1.09,
 'Repurchase Rate (%)': 8.41}
```

In [112…

```
# Display repurchase rate 2021
repurchase_rate_2021 = get_repurchase_rate(satisfied_2021)
```

```
print('Repurchase Rate 2021')
repurchase_rate_2021
```

```
Repurchase Rate 2021
```

Out[112…

```
{'Total Purchases': 44528,
 'Unique Customers': 39719,
 'Avg Purchases per Customer (%)': 1.12,
 'Repurchase Rate (%)': 10.8}
```

In [113…

```
# Average yearly Repurchase Rate
avg_repurchase_rate = (repurchase_rate_2021['Repurchase Rate (%)'] + repurchase_rate_2020['Repurchase Rat
print(f"Estimated Repurchase Rate: {avg_repurchase_rate:.2f}%")
```

```
Estimated Repurchase Rate: 9.61%
```

Average Order Value

In [115…

```
# Check class flight value
satisfaction_data['Class'].unique()
```

Out[115…

```
array(['Eco Plus', 'Business', 'Eco'], dtype=object)
```

To determine `Revenue`, two variables that is used to assume are `Class` for ticket base fare and `Flight Distance`. Base price and coefficient for the variables are:

1. Class Coefficients:

- Eco: `$500`
- Eco Plus: `$1000`
- Business: `$5000`

2. Flight Distance Coefficients:

- Short flights (0 - 1499 miles): 0.8
- Medium flights (1500 - 2999 miles): 1.0
- Long flights (>= 3000 miles): 1.5.

To calculate the `Average Order Value (AOV)` using the estimated revenue, here is the formula:

$$AOV = \frac{\text{Total Revenue}}{\text{Total Orders}}$$

In [117…

```
# Create a function to get coefficient distance
def get_distance_coefficient(distance, flight_class):
    """
    Determines the distance coefficient based on flight distance.

    Parameters
    ----------
    distance : float
        The flight distance in kilometers.

    flight_class : str
        The class of the flight (not used in the current logic but included for potential future use).

    Returns
    -------
    float
        The distance coefficient:
        - 0.8 for distances < 1500 km
        - 1.0 for distances between 1500 and 3000 km
        - 1.5 for distances >= 3000 km
    """
```

```python
    if distance < 1500:
        return 0.8
    elif 1500 <= distance < 3000:
        return 1.0
    else:
        return 1.5

# Create a function to calculate estimated revenue
def get_revenue(row):
    """
    Calculates revenue based on flight class and distance.

    Parameters
    ----------
    row : pandas.Series
        A row from the DataFrame containing 'Class' and 'Flight Distance'.

    Returns
    -------
    float
        The calculated revenue based on the base price and distance coefficient.
    """
    base_price = base_prices.get(row['Class'])
    distance_coefficient = get_distance_coefficient(row['Flight Distance'], row['Class'])
    revenue = base_price * distance_coefficient
    return revenue
```

In [118…

```python
# Define base prices for each class
base_prices = {
    'Eco': 500,
    'Eco Plus': 1000,
    'Business': 5000
}
```

In [119…

```python
# Apply the function to the DataFrame
satisfied_2020['Estimated Revenue'] = satisfied_2020.apply(get_revenue, axis=1)
satisfied_2021['Estimated Revenue'] = satisfied_2021.apply(get_revenue, axis=1)
satisfied_all['Estimated Revenue'] = satisfied_all.apply(get_revenue, axis=1)

satisfied_all[['Class', 'Flight Distance', 'Estimated Revenue']]
```

Out[119…

	Class	Flight Distance	Estimated Revenue
0	Business	3758	7500.0
1	Eco	641	400.0
2	Business	1127	4000.0
3	Business	1765	5000.0
4	Business	3145	7500.0
...	...	...	...
78605	Business	528	4000.0
78606	Business	950	4000.0
78607	Eco	216	400.0
78608	Business	2629	5000.0
78609	Business	3178	7500.0

78610 rows × 3 columns

In [120…

```python
#Create a function to calculate AOV
def get_aov(data):
```

```python
    """
    Calculates total revenue, total orders, and Average Order Value (AOV).

    Parameters
    ----------
    data : pandas.DataFrame
        DataFrame containing order data, including revenue values.

    Returns
    -------
    dict
        Dictionary containing:
        - 'total_revenue': Sum of all revenue values.
        - 'total_orders': Number of orders.
        - 'AOV': Average Order Value (total revenue divided by total orders).
    """

    total_revenue = data['Estimated Revenue'].sum()

    total_orders = len(data)

    aov = total_revenue / total_orders if total_orders > 0 else 0
    aov = round(aov,2)

    return {
        "Total Revenue ($)": total_revenue,
        "Total Orders": total_orders,
        "AOV ($)": aov
    }
```

In [121…

```python
# Calculate AOV for 2020
aov_2020 = get_aov(satisfied_2020)
print('Average Order Value 2020')
aov_2020
```

```
Average Order Value 2020
```

Out[121…

```
{'Total Revenue ($)': 135949650.0, 'Total Orders': 34082, 'AOV ($)': 3988.9}
```

In [122…

```python
# Calculate AOV for 2021
aov_2021 = get_aov(satisfied_2021)
print('Average Order Value 2021')
aov_2021
```

```
Average Order Value 2021
```

Out[122…

```
{'Total Revenue ($)': 177329600.0, 'Total Orders': 44528, 'AOV ($)': 3982.43}
```

In [123…

```python
# Average yearly AOV
avg_aov = (aov_2021['AOV ($)'] + aov_2020['AOV ($)']) / 2
print(f"Estimated Repurchase Rate: ${avg_aov:.2f}")
```

```
Estimated Repurchase Rate: $3985.66
```

Cost of Repurchase Customer

There are several methods to assume Customer Retention Cost:

- `AOV percentage` : Assume that a repurchase customer costs a percentage of the Average Order Value (AOV).
- `Fixed Cost per Repurchase` : Assume a fixed cost per returning customer based on industry benchmarks.
- `Discount-Based Approach` : If repurchase customers get discounts, assume that as a cost.
- `Churn-Based Assumption` : If only X% of customers repurchase, distribute the total retention cost across them.

To simplify the assumption, the first approach will be used, with retention cost at `0.5% of AOV`.

$$\text{Retention Cost per Repurchase} = \text{AOV} \times 0.005$$

In [126…

```
#Create function to calculate repurchase cost
def get_repurchase_cost(aov, rep_coef):
    """
    Calculates the assumed retention cost per repurchase.

    Parameters
    ----------
    aov : float
        The Average Order Value (AOV).

    rep_coef : float
        The retention cost coefficient (percentage of AOV considered as repurchase cost).

    Returns
    -------
    float
        The calculated retention cost per repurchase.
    """

    cost_repurchase = aov * rep_coef

    return cost_repurchase
```

In [127…

```
aov = aov_2020['AOV ($)']
rep_coef = 0.005

rep_cost_2020 = get_repurchase_cost(aov = aov,
                                     rep_coef = rep_coef)

print(f"Assumed Cost per Repurchase 2020: ${rep_cost_2020:.2f}")
```

```
Assumed Cost per Repurchase 2020: $19.94
```

In [128…

```
aov = aov_2021['AOV ($)']
rep_coef = 0.005

rep_cost_2021 = get_repurchase_cost(aov = aov,
                                     rep_coef = rep_coef)

print(f"Assumed Cost per Repurchase 2021: ${rep_cost_2021:.2f}")
```

```
Assumed Cost per Repurchase 2021: $19.91
```

In [129…

```
# Average yearly retention cost
avg_cost_per_repurchase = (rep_cost_2021 + rep_cost_2020) / 2
print(f"Estimated Cost of Repurchase: ${avg_cost_per_repurchase:.2f}")
```

```
Estimated Cost of Repurchase: $19.93
```

Dissatisfied Class Data

The datasets provide all the features that are available in Task 1 with additional column `Churn` in year 2020 and 2021. This data respresents only `Dissatisfied` customer which will be used on the business metrics.

Import Data

In [133…

```
dissatisfied_1 = read_data(path = 'churn_data_2020_q1.csv')
dissatisfied_2 = read_data(path = 'churn_data_2020_q2.csv')
dissatisfied_3 = read_data(path = 'churn_data_2020_q3.csv')
dissatisfied_4 = read_data(path = 'churn_data_2020_q4.csv')

dissatisfied_5 = read_data(path = 'churn_data_2021_q1.csv')
dissatisfied_6 = read_data(path = 'churn_data_2021_q2.csv')
```

```
dissatisfied_7 = read_data(path = 'churn_data_2021_q3.csv')
dissatisfied_8 = read_data(path = 'churn_data_2021_q4.csv')
```

```
Data shape : (22809, 25)
Data shape : (29364, 25)
Data shape : (32625, 25)
Data shape : (23216, 25)
Data shape : (18312, 25)
Data shape : (26187, 25)
Data shape : (28635, 25)
Data shape : (35583, 25)
```

In [134...

```
# Concat yearly data
dissatisfied_2020 = pd.concat([dissatisfied_1,dissatisfied_2 ,dissatisfied_3 ,dissatisfied_4], ignore_ind
dissatisfied_2021 = pd.concat([dissatisfied_5 ,dissatisfied_6 ,dissatisfied_7 ,dissatisfied_8], ignore_in

# Concat all data
dissatisfied_all = pd.concat([dissatisfied_2020,dissatisfied_2021], ignore_index=True)
```

In [135...

```
# Display satisfied data 2020
print(f'Dissatisfied 2020 data shape: {dissatisfied_2020.shape}')
dissatisfied_2020.head()
```

```
Dissatisfied 2020 data shape: (108014, 25)
```

Out[135...

	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	...	On-board service
0	64556	Male	Loyal Customer	59	Personal Travel	Eco	710	1	5	1	...	3
1	100379	Female	Loyal Customer	61	Personal Travel	Eco	310	2	4	2	...	4
2	102044	Female	Loyal Customer	46	Personal Travel	Eco	1041	1	5	1	...	5
3	153566	Male	disloyal Customer	26	Business travel	Business	1587	3	3	3	...	4
4	72989	Female	disloyal Customer	34	Business travel	Eco	253	1	0	1	...	4

5 rows × 25 columns

In [136...

```
# Display satisfied data 2020
print(f'Dissatisfied 2021 data shape: {dissatisfied_2021.shape}')
dissatisfied_2021.head()
```

```
Dissatisfied 2021 data shape: (108717, 25)
```

Out[136…

	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	...	On-board service	r… se…
0	101761	Female	disloyal Customer	23	Business travel	Eco	859	2	2	2	...	5	
1	110879	Male	Loyal Customer	55	Personal Travel	Eco	1111	3	5	3	...	4	
2	32282	Male	disloyal Customer	30	Business travel	Eco	448	2	2	2	...	3	
3	52252	Female	Loyal Customer	28	Personal Travel	Eco	129	1	3	1	...	3	
4	40931	Male	Loyal Customer	58	Personal Travel	Eco	472	2	5	2	...	1	

5 rows × 25 columns

In [137…

```
#Check if ID is unique
print(f'Number of unique customer: {dissatisfied_all.id.nunique()}')
```

```
Number of unique customer: 131525
```

Business Metrics Assumption

Churn Rate

The churn rate measures the percentage of customers who stop using a service over a period of time. It is measured by number of customers who churned divided by total unique customers.

$$\text{Churn Rate} = \frac{\text{Number of Churned Customers}}{\text{Total Unique Customers}} \times 100\%$$

In [141…

```
dissatisfied_2020['churn'].unique()
```

Out[141…

```
array(['Churn', 'Not Churn'], dtype=object)
```

In [142…

```
# Create a function to calculate churn rate
def get_churn_rate(data):
    """
    Calculates the churn rate based on unique customer activity.

    Parameters
    ----------
    data : pandas.DataFrame
        DataFrame containing customer IDs and churn status.

    Returns
    -------
    dict
        Dictionary containing:
        - 'churned_customers': Number of customers who have churned.
        - 'non_churned_customers': Number of active customers.
        - 'churn_rate': Proportion of churned customers to total customers.
    """
    # Count unique customers
    total_unique_customers = data['id'].nunique()

    # Count unique churned customers
    churned_customers = data[data['churn'] == 'Churn']['id'].nunique()

    # Calculate churn rate
```

```
    churn_rate = (churned_customers / total_unique_customers) * 100 if total_unique_customers > 0 else 0
    churn_rate = round(churn_rate, 2)

    return {
        "Churned Customers": churned_customers,
        "Total Unique Customer": total_unique_customers,
        "Churn Rate (%)": churn_rate
    }
```

In [143…

```
churn_2020 = get_churn_rate(data = dissatisfied_2020)
print('Total Churn 2020')
churn_2020
```

```
Total Churn 2020
```

Out[143…

```
{'Churned Customers': 72237,
 'Total Unique Customer': 85581,
 'Churn Rate (%)': 84.41}
```

In [144…

```
churn_2021 = get_churn_rate(data = dissatisfied_2021)
print('Total Churn 2021')
churn_2021
```

```
Total Churn 2021
```

Out[144…

```
{'Churned Customers': 72095,
 'Total Unique Customer': 85564,
 'Churn Rate (%)': 84.26}
```

In [145…

```
# Average yearly churn rate
avg_churn_rate = (churn_2021['Churn Rate (%)'] + churn_2020['Churn Rate (%)']) / 2
print(f"Estimated Cost of Repurchase: {avg_churn_rate:.2f}%")
```

```
Estimated Cost of Repurchase: 84.34%
```

Cost Acquisition Cost

The `Customer Acquisition Cost (CAC)` estimates how much it costs to acquire a new customer. Generally, it calculates the total marketing cost to gain new customers with formula as follow:

$$CAC = \frac{\text{Total Marketing Cost}}{\text{Number of New Customers}}$$

With no marketing cost information in the data, the certain percentage of total revenue as a marketing cost. So, total marketing cost formula is as below:

$$\text{Total Revenue} = \text{AOV} \times \text{Total Transaction}$$

$$\text{Estimated Marketing Cost} = \text{Total Revenue} \times \text{Marketing Spend } \backslash\%$$

In defining `Customer Acquisition Cost (CAC)` the AOV is derived from dissatisfied customers data rather than the satisfied ones. Because, knowing their spending behavior before churning is more relevant to understand how much value that can be extracted from them. Hence it is better to use so it will not overestimate profitability.

Also, in this case, the marketing coefficient is `1% of the Total Revenue`.

In [149…

```
# Apply AOV to dissatisfied customer1 year 2020
dis_2020 = dissatisfied_2020.copy()
dis_2020['Estimated Revenue'] = dis_2020.apply(get_revenue, axis=1)

aov_2020_dis = get_aov(dis_2020)
print('Average Order Value 2020')
aov_2020_dis
```

```
Average Order Value 2020
```

Out[149… {'Total Revenue ($)': 168211350.0, 'Total Orders': 108014, 'AOV ($)': 1557.31}

In [150…
```
# # Apply AOV to dissatisfied customers year 2021
dis_2021 = dissatisfied_2021.copy()
dis_2021['Estimated Revenue'] = dis_2021.apply(get_revenue, axis=1)

aov_2021_dis = get_aov(dis_2021)
print('Average Order Value 2021')
aov_2021_dis
```

Average Order Value 2021

Out[150… {'Total Revenue ($)': 170581150.0, 'Total Orders': 108717, 'AOV ($)': 1569.04}

In [151…
```
# Create Customers Acquisition Cost function
def get_cac(data, aov, cac_coef):
    """
    Estimates Customer Acquisition Cost (CAC) using AOV and marketing spend percentage.

    Parameters
    ----------
    data : pandas.DataFrame
        DataFrame containing transaction data.

    aov : float
        Average Order Value (AOV).

    cac_coef : float
        Assumed percentage of revenue allocated to customer acquisition (e.g., 0.1 for 10%).

    Returns
    -------
    float
        Estimated Customer Acquisition Cost (CAC).
    """

    # Calculate the number of unique new customers
    new_customers = data['id'].nunique()

    # Estimate total revenue
    total_revenue = aov * len(data)

    # Estimate marketing cost
    estimated_marketing_cost = total_revenue * cac_coef

    # Calculate CAC
    cac = estimated_marketing_cost / new_customers if new_customers > 0 else 0
    cac = round(cac, 2)

    return cac
```

In [152…
```
#Diplay Customer Acquisition Cost for 2020
marketing_percentage = 0.01

cac_2020  = get_cac(data = dissatisfied_2020,
                    aov = aov_2020_dis['AOV ($)'],
                    cac_coef = marketing_percentage)

print(f"Assumed Customer Acquisiton Cost 2020: ${cac_2020:.2f}")
```

Assumed Customer Acquisiton Cost 2020: $19.66

In [153…
```
#Diplay Customer Acquisition Cost for 2021

cac_2021  = get_cac(data = dissatisfied_2021,
                    aov = aov_2021_dis['AOV ($)'],
                    cac_coef = marketing_percentage)
```

```python
print(f"Assumed Customer Acquisiton Cost 2021: ${cac_2021:.2f}")
```

```
Assumed Customer Acquisiton Cost 2021: $19.94
```

In [154…

```python
#Diplay average Customer Acquisition Cost

avg_cac = (cac_2020 + cac_2021) / 2

print(f"Assumed Customer Acquisition Cost: ${avg_cac:.2f}")
```

```
Assumed Customer Acquisition Cost: $19.80
```

Simulation Metrics

Status	Metrics	
Satisfied	Repurchase Rate *Percentage of aviation customer who book again*	9.61%
Satisfied	Average Order Value (AOV) *Percentage of aviation customer who book again*	$3985.66
Satisfied	Cost of Repurchase Customer *Percentage of aviation customer who book again*	$19.93
Dissatisfied	Churn Rate *Percentage of aviation customer who book again*	84.34%
Dissatisfied	Customer Acquisition Cost *Percentage of aviation customer who book again*	$19.80

Build Metrics for Simulation Summary

`Repurchase Rate`
The repurchase rate within a year (where cross year is not considered) in 2020 and 2021 is somewhere between `8.41%` to `10.80%`, while within both year the total rate would be around 16% with 1.2 average purchase per customer. Meaning there are more likely cross-year repurchase activity from the customers. However, it is safer to use the average of both year, in which lies at `9.61% yearly repurchase rate`.

`Average Order Value Summary`
The AOV within a year in 2020 and 2021 are pretty close to each other with `$3988.90` and `$3982.43`. The average of both year is `$3985.66 yearly AOV`.

`Cost of Repurchase`
The repurchase cost, assuming 0.5% of the AOV, averaging from 2020 and 2021 is at `$19.93`.

`Churn Rate`
The Churn Rate betweeeen year 2020 and 2021 are similar with `84.41%` and `84.26%`. The average for both churn rate is `84.34% Churn Rate` of dissatisfid customers.

`Customer Acquisition Cost`
With the average AOV of $1563 fordissatisfiedcustomerin2020to2021, alongwith 119.79$`.

Task 5: Simulation

Based on `business metrics` defined in previous task, there are several value to be added to the simulation:

`Expected Revenue from Repurchase Customers`

$$E[revenue] = n_{satisfied\_cust} \times repurchase\_rate \times AOV$$

`Expected Cost for Repurchase Customers`
$E[cost\_repurchase] = n_{satisfied\_cust} \times cost\_repurchase$

`Expected Cost to Acquire Customers`
$E[cost\_acquiring] = n_{dissatisfied\_cust} \times churn\_rate \times CAC$

`Net Profit Calculation`
$Net\_profit = E[revenue] - E[cost\_repurchase] - E[cost\_acquiring]$

Rule-Based Revenue and Cost Simulation

Using `data_simulation.csv` dataset, the estimated revenue and cost simulation will be applied using `rule-based model` defined from Task 3.

Load Data

In [162…
```
#Import Data
simulation_data = read_data(path = 'data_simulation.csv')
```
```
Data shape : (25893, 23)
```

In [163…
```
simulation_data.head()
```

Out[163…

	id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	...	Seat comfort
0	19556	Female	Loyal Customer	52	Business travel	Eco	160	5	4	3	...	3
1	90035	Female	Loyal Customer	36	Business travel	Business	2863	1	1	3	...	5
2	12360	Male	disloyal Customer	20	Business travel	Eco	192	2	0	2	...	2
3	77959	Male	Loyal Customer	44	Business travel	Business	3377	0	0	0	...	4
4	36875	Female	Loyal Customer	49	Business travel	Eco	1182	2	3	4	...	2

5 rows × 23 columns

Pre-process Data

In [165…
```
X_val = simulation_data.copy()

# Encode categorical data
cat_features = list(cat_cols)

encoder, X_val = encoding_cat_feature(data = train_set,
                                      fit = False,
                                      encoder = encoder)

# show train_set (shanity check)
X_val.head()
```

Out[165…

	Age	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	Food and drink	Online boarding	Seat comfort	Inflight entertainment	...	Che ser
0	13	460	3	4	3	1	5	3	5	5	...	
1	25	235	3	2	3	3	1	3	1	1	...	
2	26	1142	2	2	2	2	5	5	5	5	...	
3	25	562	2	5	5	5	2	2	2	2	...	
4	61	214	3	3	3	3	4	5	5	3	...	

5 rows × 23 columns

Apply Rule-Based Model

In [167…

```
# Copy X to avoid modifying the original data
X_rb = X_val.copy()

# Apply the rule-based classification function
X_rb['satisfaction'] = X_rb.apply(classify_satisfaction_rule_based, axis=1)

# Show applied rule
X_rb_features = X_ruled[['Online boarding', 'Inflight wifi service',
                    'Type of Travel_Personal Travel', 'Class_Eco',
                    'Inflight entertainment', 'satisfaction']]

X_ruled_features.head()
```

Out[167…

	Online boarding	Inflight wifi service	Type of Travel_Personal Travel	Class_Eco	Inflight entertainment	satisfaction
0	3	3	1.0	0.0	5	Satisfied
1	3	3	0.0	0.0	1	Satisfied
2	5	2	0.0	0.0	5	Satisfied
3	2	2	0.0	0.0	2	Dissatisfied
4	5	3	0.0	0.0	3	Satisfied

Calculate the Simulation

In [169…

```
# Create Revenue and Cost Simulation calculation funtion
def calculate_financial_metrics(data, repurchase_rate, aov, cost_repurchase, churn_rate, cac):
    """
    Calculates key financial metrics, including expected revenue, repurchase cost, acquisition cost, and

    Parameters
    ----------
    data : pandas.DataFrame
        DataFrame containing order data.

    repurchase_rate : float
        The proportion of customers expected to make a repeat purchase.

    aov : float
        Average Order Value (AOV).

    cost_repurchase : float
        Cost incurred per repurchase.

    churn_rate : float
```

```
        The proportion of customers who stop purchasing.

    cac : float
        Customer Acquisition Cost (CAC).

    Returns
    -------
    dict
        Dictionary containing:
        - 'expected_revenue': Total expected revenue based on AOV and customer retention.
        - 'expected_repurchase_cost': Total cost of repurchases.
        - 'expected_acquisition_cost': Total acquisition cost for new customers.
        - 'net_profit': Expected revenue minus repurchase and acquisition costs.
    """

    # Count satisfied and dissatisfied customers
    n_satisfied_cust = data[data['satisfaction'] == 'Satisfied'].shape[0]
    n_dissatisfied_cust = data[data['satisfaction'] == 'Dissatisfied'].shape[0]

    # Calculate financial metrics
    expected_revenue = n_satisfied_cust * repurchase_rate * aov
    expected_revenue = round(expected_revenue, 2)

    expected_cost_repurchase = n_satisfied_cust * cost_repurchase
    expected_cost_repurchase = round(expected_cost_repurchase, 2)

    expected_cost_acquiring = n_dissatisfied_cust * churn_rate * cac
    expected_cost_acquiring = round(expected_cost_acquiring, 2)

    net_profit = expected_revenue - expected_cost_repurchase - expected_cost_acquiring
    net_profit = round(net_profit, 2)

    return {
        "Total Satisfied Customers": n_satisfied_cust,
        "Total Dissatisfied Customers": n_dissatisfied_cust,
        "Expected Revenue ($)": expected_revenue,
        "Expected Cost Repurchase ($)": expected_cost_repurchase,
        "Expected Cost Acquiring ($)": expected_cost_acquiring,
        "Net Profit ($)": net_profit
    }
```

In [170…

```
# Define the metrics
repurchase_rate = 9.61/100
aov = 3985.66
cost_repurchase = 19.93
churn_rate = 84.34/100
cac = 19.80
```

In [171…

```
# Calculate the Rule-Based simulation
X_rb_simulation = calculate_financial_metrics (data = X_rb,
                                               repurchase_rate = repurchase_rate,
                                               aov = aov,
                                               cost_repurchase = cost_repurchase,
                                               churn_rate = churn_rate,
                                               cac = cac)

X_rb_simulation
```

Out[171…

```
{'Total Satisfied Customers': 69065,
 'Total Dissatisfied Customers': 34529,
 'Expected Revenue ($)': 26453409.32,
 'Expected Cost Repurchase ($)': 1376465.45,
 'Expected Cost Acquiring ($)': 576610.82,
 'Net Profit ($)': 24500333.05}
```

Machine Learning Revenue and Cost Simulation

The dataset used for training the interpretable machine learning model will be `satisfaction_df.csv`. The `data_simulation.csv` data set then will be used to predict satisfactory customer classification which later revenue and cost simulation metrics will be applied to.

For this case, the machine learning model to use is `Random Forest Classifier`. The workflow of this Machine Learning process are:

1. Split training data

Since `simulation_data.csv` has no satisfaction label, split the training data into a smaller training set and a validation set is necessary for ML developmnet.

2. Train the model

Train the `Random Forest` model on the training set.

3. Evaluate training model

Evaluate the model's performance on training validation set using performance metrics like accuracy, precision, recall, F1-score, and ROC-AUC.

4. Predicts on simulation dataset

Use the trained model to generate predictions on simulation data.

5. Simulate the simulation dataset

Once satisfaction labels of the simulation data is available, calculate the result.

Machine Learning Modeling

In [176…

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score
from sklearn.metrics import confusion_matrix
```

Split training data

In [178…

```
X_train, X_train_val, y_train, y_train_val = train_test_split (X_encoded, y_train_encoded,
                                                                test_size = 0.2,
                                                                random_state = 123)
```

Train the model

In [180…

```
# Random Forest Model
rf = RandomForestClassifier(random_state = 42)

# Train the model
rf.fit(X_train, y_train)
```

Out[180…

```
▾ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

Evaluate the training model

In [182…

```
#Create evaluation performance model function
def evaluate_model(y_true, y_pred, model_name):
    print(f"Evaluation for {model_name}:")
    print(f"Accuracy: {accuracy_score(y_true, y_pred)}")
```

```
    print(f"Precision: {precision_score(y_true, y_pred, pos_label= 1)}")
    print(f"Recall: {recall_score(y_true, y_pred, pos_label= 1)}")
    print(f"F1-Score: {f1_score(y_true, y_pred, pos_label= 1)}")
    print(f"ROC-AUC: {roc_auc_score(y_true, y_pred == 1)}")
    print("Confusion Matrix:\n", confusion_matrix(y_true, y_pred, labels=[1, 0]))
```

In [183…

```
# Predictions to train data
y_trn_pred = rf.predict(X_train)
```

In [184…

```
# Evaluate Train prediction
evaluate_model(y_train, y_trn_pred, "Random Forest")
```

```
Evaluation for Random Forest:
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1-Score: 1.0
ROC-AUC: 1.0
Confusion Matrix:
 [[35957     0]
 [    0 46918]]
```

Using the model, the performance reach 100% accuracy for all of the scoring. This seems good, but this also mean a potential over-fitting scenario. Let's test with the validation data and look if the score has a relatively large gap.

In [186…

```
# Predict on validation set
y_trv_pred = rf.predict(X_train_val)
```

In [187…

```
evaluate_model(y_train_val, y_trv_pred, "Random Forest")
```

```
Evaluation for Random Forest:
Accuracy: 0.9610019788599836
Precision: 0.9688653136531366
Recall: 0.9398210290827741
F1-Score: 0.9541221894163071
ROC-AUC: 0.958449439747262
Confusion Matrix:
 [[ 8402   538]
 [  270 11509]]
```

Comparing on both training and training validation result shows that the prediction tends to have high accuracy, since even the training validation result gives pretty 95% overall score. This could mean that the model is a good fit.

Predicts on validation dataset

In [190…

```
# Predict on Validation dataset
y_val_pred = rf.predict(X_val)
```

In [191…

```
# Make copy
X_rf = X_val.copy()

# Insert prediction into the dataset
X_rf['satisfaction'] = y_val_pred

# Decode the target column
X_rf['satisfaction'] = X_rf['satisfaction'].map({1: 'Satisfied', 0: 'Dissatisfied'})
```

In [192…

```
X_rf.head()
```

Out[192...

	Age	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	Food and drink	Online boarding	Seat comfort	Inflight entertainment	...	Infl ser
0	13	460	3	4	3	1	5	3	5	5	...	
1	25	235	3	2	3	3	1	3	1	1	...	
2	26	1142	2	2	2	2	5	5	5	5	...	
3	25	562	2	5	5	5	2	2	2	2	...	
4	61	214	3	3	3	3	4	5	5	3	...	

5 rows × 24 columns

Simulate the Simulation Dataset

In [194...

```
# Calculate the Machine Learning simulation
X_rf_simulation = calculate_financial_metrics (data = X_rf,
                                              repurchase_rate = repurchase_rate,
                                              aov = aov,
                                              cost_repurchase = cost_repurchase,
                                              churn_rate = churn_rate,
                                              cac = cac)

X_rf_simulation
```

Out[194...

```
{'Total Satisfied Customers': 44629,
 'Total Dissatisfied Customers': 58965,
 'Expected Revenue ($)': 17093885.54,
 'Expected Cost Repurchase ($)': 889455.97,
 'Expected Cost Acquiring ($)': 984675.4,
 'Net Profit ($)': 15219754.17}
```

Simulation Summary

Although the rule-based was came with feature importance, the lack of variable and/or the base of reasoning used in the model probably is the reason the results are highly differentiate from one and another. However, we can compare it to the test data to make sure that the Rule-Based model is the one that is not accurate enough.

Task 6: Evaluate the Simulation

After simulating the revenue and cost, the ML model will be evaluated toward the `test.csv` The result will be compared to the actual result.

In [198...

```
#Import Data
test_data = read_data(path = 'test.csv')
```

```
Data shape : (25976, 24)
```

In [199...

```
# set customerID as index
test_data.set_index('id', inplace=True)
```

In [200...

```
test_data.head()
```

Out[200…

id	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	...	en
19556	Female	Loyal Customer	52	Business travel	Eco	160	5	4	3	4	...	
90035	Female	Loyal Customer	36	Business travel	Business	2863	1	1	3	1	...	
12360	Male	disloyal Customer	20	Business travel	Eco	192	2	0	2	4	...	
77959	Male	Loyal Customer	44	Business travel	Business	3377	0	0	0	2	...	
36875	Female	Loyal Customer	49	Business travel	Eco	1182	2	3	4	3	...	

5 rows × 23 columns

Predict Test Data

In [202…

```
# Split input and output
X_test, y_test = split_input_output(data = test_data,
                                    target_column = "satisfaction")
```

In [203…

```
# Define Training Dataset
test_set = pd.concat([X_test, y_test], axis=1)

# Encode categorical data
cat_features = list(cat_cols)

encoder, X_test = encoding_cat_feature(data = test_set,
                                        fit = False,
                                       encoder = encoder)

# show train_set (sanity check)
X_test.head()
```

Out[203…

	Age	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	Food and drink	Online boarding	Seat comfort	Inflight entertainment	...	Che se
0	52	160	5	4	3	4	3	4	3	5	...	
1	36	2863	1	1	3	1	5	4	5	4	...	
2	20	192	2	0	2	4	2	2	2	2	...	
3	44	3377	0	0	0	2	3	4	4	1	...	
4	49	1182	2	3	4	3	4	1	2	2	...	

5 rows × 23 columns

In [204…

```
#Encode y train data
test_label_encoder, y_test_encoded = encode_labels(y_test)
```

In [205…

```
print(test_label_encoder.classes_)
```

```
['neutral or dissatisfied' 'satisfied']
```

In [206…

```
# Predict on Validation dataset
y_test_pred = rf.predict(X_test)
```

Evaluate Prediction Test

In [208…

```
evaluate_model(y_test_encoded, y_test_pred, "Random Forest")
```

```
Evaluation for Random Forest:
Accuracy: 0.9621188789651987
Precision: 0.9715759934823934
Recall: 0.9412435324037534
F1-Score: 0.9561692650334076
ROC-AUC: 0.9598484182295992
Confusion Matrix:
 [[10733   670]
 [  314 14259]]
```

Compare the Simulation

In [210…

```
# Make copy
X_test_rf = X_test.copy()

# Insert prediction into the dataset
X_test_rf['satisfaction'] = y_test_pred

# Decode the target column
X_test_rf['satisfaction'] = X_test_rf['satisfaction'].map({1: 'Satisfied', 0: 'Dissatisfied'})
```

In [211…

```
# Calculate the predicted test data Machine Learning simulation
X_test_simulated = calculate_financial_metrics (data = X_test_rf,
                                               repurchase_rate = repurchase_rate,
                                               aov = aov,
                                               cost_repurchase = cost_repurchase,
                                               churn_rate = churn_rate,
                                               cac = cac)

X_test_simulated
```

Out[211…

```
{'Total Satisfied Customers': 11047,
 'Total Dissatisfied Customers': 14929,
 'Expected Revenue ($)': 4231243.22,
 'Expected Cost Repurchase ($)': 220166.71,
 'Expected Cost Acquiring ($)': 249304.15,
 'Net Profit ($)': 3761772.36}
```

In [212…

```
# Make copy
test_simulated = test_data.copy()

# Map the target column
test_simulated['satisfaction'] = test_simulated['satisfaction'].map({'satisfied': 'Satisfied', 'neutral o
```

In [213…

```
# Calculate the Machine Learning simulation
test_data_simulated = calculate_financial_metrics (data = test_simulated,
                                               repurchase_rate = repurchase_rate,
                                               aov = aov,
                                               cost_repurchase = cost_repurchase,
                                               churn_rate = churn_rate,
                                               cac = cac)

test_data_simulated
```

```
Out[213…  {'Total Satisfied Customers': 11403,
 'Total Dissatisfied Customers': 14573,
 'Expected Revenue ($)': 4367599.02,
 'Expected Cost Repurchase ($)': 227261.79,
 'Expected Cost Acquiring ($)': 243359.19,
 'Net Profit ($)': 3896978.04}
```

In [214…

```
X_rb_test = X_test.copy()

# Apply the rule-based classification function
X_rb_test['satisfaction'] = X_rb_test.apply(classify_satisfaction_rule_based, axis=1)

test_rb_simulated = calculate_financial_metrics (data = X_rb_test,
                                              repurchase_rate = repurchase_rate,
                                              aov = aov,
                                              cost_repurchase = cost_repurchase,
                                              churn_rate = churn_rate,
                                              cac = cac)

test_rb_simulated
```

Out[214…

```
{'Total Satisfied Customers': 17256,
 'Total Dissatisfied Customers': 8720,
 'Expected Revenue ($)': 6609426.36,
 'Expected Cost Repurchase ($)': 343912.08,
 'Expected Cost Acquiring ($)': 145618.07,
 'Net Profit ($)': 6119896.21}
```

Based on the result, it shows that the machine learning model has pretty good accuracy. This proves that the Machine Learning Prediction Model is much better that the Rule-Based Model which result is apparently far from accurate. This said, `no further comparison for the actual result to the Rule-Based Model` needed.

To get a better view, the `Comparison Results` will be presented in table below:

In [216…

```
# Create DataFrame for comparison
comparison_result = pd.DataFrame({
    'Simulation Data': X_test_simulated,
    'Actual': test_data_simulated
})

# Avoid division by zero by replacing zeros with NaN (or another strategy)
comparison_result["Difference (%)"] = abs(comparison_result["Simulation Data"] - comparison_result["Actua

# Display the corrected DataFrame
comparison_result
```

Out[216…

	Simulation Data	Actual	Difference (%)
Total Satisfied Customers	11047.00	11403.00	3.121985
Total Dissatisfied Customers	14929.00	14573.00	2.442874
Expected Revenue ($)	4231243.22	4367599.02	3.121985
Expected Cost Repurchase ($)	220166.71	227261.79	3.121985
Expected Cost Acquiring ($)	249304.15	243359.19	2.442875
Net Profit ($)	3761772.36	3896978.04	3.469501

Evaluation Summary

The `machine learning model` gives results that are close to the actual data, showing a small drop in satisfied customers and revenue, with a similar loss. On the other hand, the `rule-based model` predicts a much higher number of satisfied customers, lower costs, and a big profit, which might be too optimistic. The ML model is better for making realistic predictions, while the rule-based model is more useful for setting business goals and estimating potential best-case scenarios.

Task 7: Variable Simulation

This section is to understand on how any variable affecting satisfaction rate.

In [221…

```python
from sklearn.linear_model import LogisticRegression

# Train a Logistic Regression model
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

```
D:\Application\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:469: ConvergenceWarning: lbfg
s failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[221…

```
▾ LogisticRegression
LogisticRegression()
```

In [222…

```python
# Create function to get coefficient from Logreg model
def get_coef_df(X, lr):
    """
    Retrieves linear regression coefficients as a DataFrame.

    Parameters
    ----------
    X : pandas.DataFrame
        Input features used in model training.

    lr : sklearn.linear_model.LinearRegression
        A fitted LinearRegression model.

    Returns
    -------
    pandas.DataFrame
        DataFrame with two columns: "Feature" and "Coefficient".
    """

    # Create a DataFrame for coefficients
    coef_df = pd.DataFrame({
        "Feature": X.columns,
        "Coefficient": lr.coef_
    })

    # Create a DataFrame for the intercept
    intercept_df = pd.DataFrame({
        "Feature": ["Intercept"],
        "Coefficient": [lr.intercept_]
    })

    # Concatenate the two DataFrames
    coef_df = pd.concat([coef_df, intercept_df], ignore_index=True)

    return coef_df
```

In [223…

```python
def get_coef_df_logistic(X, logreg):
    """
```

```
    Function to get logistic regression coefficients in dataframe format

    Parameters
    ----------
    X:  <pandas dataframe>
        The input features

    logreg: <LogisticRegression object>
            A fitted instance of the LogisticRegression class from scikit-learn.

    Return
    ------
    coef_df:  <pandas dataframe>
              A DataFrame with two columns: "Feature" and "Coefficient".
    """
    # Create a DataFrame for coefficients
    coef_df = pd.DataFrame({
        "Feature": X.columns,
        "Coefficient": logreg.coef_[0]
    })

    # Create a DataFrame for the intercept
    intercept_df = pd.DataFrame({
        "Feature": ["Intercept"],
        "Coefficient": [logreg.intercept_[0]]
    })

    # Concatenate the two DataFrames
    coef_df = pd.concat([coef_df, intercept_df], ignore_index=True)

    return coef_df
```

In [224…

```
# Get coefficients
coef_df = get_coef_df_logistic(X_train, logreg)
coef_df = coef_df.sort_values(by = 'Coefficient', ascending = False)

coef_df
```

Out[224...

	Feature	Coefficient
7	Online boarding	0.708825
2	Inflight wifi service	0.414443
9	Inflight entertainment	0.296252
10	On-board service	0.206264
11	Leg room service	0.162472
4	Ease of Online booking	0.074937
8	Seat comfort	0.030724
16	Departure Delay in Minutes	0.008086
1	Flight Distance	0.000209
17	Arrival Delay in Minutes	-0.013203
0	Age	-0.019717
13	Checkin service	-0.026622
15	Cleanliness	-0.085813
22	Class_Eco Plus	-0.098862
18	Gender_Male	-0.110956
12	Baggage handling	-0.155558
14	Inflight service	-0.188216
5	Gate location	-0.308058
23	Intercept	-0.309316
19	Customer Type_disloyal Customer	-0.318037
3	Departure/Arrival time convenient	-0.341982
6	Food and drink	-0.373651
20	Type of Travel_Personal Travel	-0.655106
21	Class_Eco	-0.729144

Variable Summary

- A `positive coefficient` means that an increase in the feature value is associated with an increase in the log-odds of customer satisfaction.

In other words, higher values of the feature make it more likely that the customer is satisfied.

- A `negative coefficient` means that an increase in the feature value is associated with a decrease in the log-odds of customer satisfaction.

In other words, higher values of the feature make it less likely that the customer is satisfied.

A one-unit increase in the Online boarding rating is associated with an increase of 0.708825 in the log-odds of customer satisfaction. This means that customers who rate Online boarding higher are more likely to be satisfied. On the contrary, one customer board on a economy class contributes with a 0.729144 decrease the satisfaction score.