```
In [1]: # Generic inputs for most ML tasks
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        from sklearn.model_selection import train_test_split
        from sklearn.linear_model import LinearRegression
        # This is new
        from sklearn.linear_model import LogisticRegression
        from sklearn.linear_model import Ridge
        from sklearn.linear model import Lasso
        from sklearn.ensemble import RandomForestRegressor
        pd.options.display.float_format = '{:,.2f}'.format
        # setup interactive notebook mode
        from IPython.core.interactiveshell import InteractiveShell
        InteractiveShell.ast_node_interactivity = "all"
        from IPython.display import display, HTML
```

/Users/saisrivishwanath/anaconda3/lib/python3.11/site-packages/pandas/core/arrays/masked.py:60: Use rWarning: Pandas requires version '1.3.6' or newer of 'bottleneck' (version '1.3.5' currently insta lled).

from pandas.core import (

Read and pre-process data

Out[2]:

	satisfaction	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Seat comfort	Departure/Arrival time convenient	Food and drink	 Online support	Ease of Online booking	On- board service	٤
0	satisfied	Female	Loyal Customer	65	Personal Travel	Eco	265	0	0	0	 2	3	3	_
1	satisfied	Male	Loyal Customer	47	Personal Travel	Business	2464	0	0	0	 2	3	4	
2	satisfied	Female	Loyal Customer	15	Personal Travel	Eco	2138	0	0	0	 2	2	3	
3	satisfied	Female	Loyal Customer	60	Personal Travel	Eco	623	0	0	0	 3	1	1	
4	satisfied	Female	Loyal Customer	70	Personal Travel	Eco	354	0	0	0	 4	2	2	

5 rows × 23 columns

```
In [3]: print("The column names in the dataframe are")
        list(airline_data.columns)
        The column names in the dataframe are
Out[3]: ['satisfaction',
          'Gender',
         'Customer Type',
         'Age',
         'Type of Travel',
         'Class',
         'Flight Distance',
         'Seat comfort',
          'Departure/Arrival time convenient',
         'Food and drink',
         'Gate location',
         'Inflight wifi service',
         'Inflight entertainment',
         'Online support',
         'Ease of Online booking',
          'On-board service',
          'Leg room service',
         'Baggage handling',
         'Checkin service',
         'Cleanliness',
         'Online boarding',
         'Departure Delay in Minutes',
          'Arrival Delay in Minutes']
In [4]: airline_data.isna().sum()
Out[4]: satisfaction
                                                0
        Gender
                                                0
        Customer Type
                                                0
        Age
        Type of Travel
                                                0
        Class
                                                0
        Flight Distance
                                                0
        Seat comfort
                                                0
        Departure/Arrival time convenient
                                                0
        Food and drink
                                                0
        Gate location
        Inflight wifi service
                                                0
        Inflight entertainment
                                                n
        Online support
                                                0
        Ease of Online booking
                                                0
        On-board service
                                                0
        Leg room service
                                                0
        Baggage handling
        Checkin service
                                                0
        Cleanliness
                                                0
        Online boarding
                                                0
        Departure Delay in Minutes
                                                0
        Arrival Delay in Minutes
                                              393
        dtype: int64
```

We're identifying and removing any null values, notably within the 'Arrival Delay in Minutes' column, which contains 393 missing entries. Consequently, these will be eliminated in the following step.

```
In [5]: airline_data = airline_data.dropna()
airline_data.head()
```

Out[5]:

	satisfaction	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Seat comfort	Departure/Arrival time convenient	Food and drink	 Online support	Ease of Online booking	On- board service	•
0	satisfied	Female	Loyal Customer	65	Personal Travel	Eco	265	0	0	0	 2	3	3	
1	satisfied	Male	Loyal Customer	47	Personal Travel	Business	2464	0	0	0	 2	3	4	
2	satisfied	Female	Loyal Customer	15	Personal Travel	Eco	2138	0	0	0	 2	2	3	
3	satisfied	Female	Loyal Customer	60	Personal Travel	Eco	623	0	0	0	 3	1	1	
4	satisfied	Female	Loyal Customer	70	Personal Travel	Eco	354	0	0	0	 4	2	2	

5 rows × 23 columns

```
In [73]: len(airline_data)
```

Out[73]: 129487

After eliminating rows with Null values, there are 129,487 data entries available.

```
In [6]: airline_data = airline_data.drop(columns = ['satisfaction'], axis=1)
```

```
In [7]: print("Number of rows in the dataframe are",airline_data.shape[0])
```

Number of rows in the dataframe are 129487

```
In [8]: airline_data.dtypes
```

Out[8]:		object
	Customer Type	object
	Age	int64
	Type of Travel	object
	Class	object
	Flight Distance	int64
	Seat comfort	int64
	Departure/Arrival time convenient	int64
	Food and drink	int64
	Gate location	int64
	Inflight wifi service	int64
	Inflight entertainment	int64
	Online support	int64
	Ease of Online booking	int64
	On-board service	int64
	Leg room service	int64
	Baggage handling	int64
	Checkin service	int64
	Cleanliness	int64
	Online boarding	int64
	Departure Delay in Minutes	int64
	Arrival Delay in Minutes	float64
	dtype: object	

Binary Logistic Regression

```
In [9]: Y = airline_data['Class']
```

```
In [10]: X = airline_data
print("Number of features in the dataframe are", X.shape[1])
```

```
In [11]: categorical columns = X.select dtypes(include=['object']).columns
         print("Categorical columns after excluding the dependent column:", categorical columns)
          Categorical columns after excluding the dependent column: Index(['Gender', 'Customer Type', 'Type o
          f Travel', 'Class'], dtype='object')
          Applying OneHotEncoder on the catogorical independent variables i.e., Gender, Customer Type, Type of Travel.
In [12]: gender values = airline data['Gender'].unique()
         print("Set of values for 'gender':", gender_values)
          # To get unique values for the 'color' categorical variable
         customer_type_values = airline_data['Customer Type'].unique()
         print("Set of values for 'customer_type':", customer_type_values)
          # To get unique values for the 'clarity' categorical variable
          travel_type_values = airline_data['Type of Travel'].unique()
         print("Set of values for 'travel type':", travel type values)
          Set of values for 'gender': ['Female' 'Male']
          Set of values for 'customer_type': ['Loyal Customer' 'disloyal Customer']
          Set of values for 'travel type': ['Personal Travel' 'Business travel']
In [13]: from sklearn.preprocessing import OneHotEncoder
         def get_ohe(df, col):
              ohe = OneHotEncoder(drop='first', handle_unknown='error', sparse_output=False, dtype='int')
              ohe.fit(df[[col]])
              temp df = pd.DataFrame(data=ohe.transform(df[[col]]), columns=ohe.get feature names out())
              # If you have a newer version, replace with columns=ohe.get feature names out()
              df.drop(columns=[col], axis=1, inplace=True)
              df = pd.concat([df.reset_index(drop=True), temp_df], axis=1)
              return df
In [15]: airline_data.head()
Out[15]:
                                                     Food
                                                                  Inflight
                                                                                                Leg
                                   Seat Departure/Arrival
                                                             Gate
                                                                             Inflight Online
                                                                                                    Baggage Checkin
                           Fliaht
             Age
                   Class
                                                      and
                                                                    wifi
                                                                                               room
                                                                        entertainment support ...
                        Distance
                                comfort
                                        time convenient
                                                          location
                                                                                                    handling
                                                                                                            service
                                                     drink
                                                                 service
                                                                                             service
                                                               2
              65
                    Fco
                            265
                                     O
                                                   O
                                                        O
                                                                      2
                                                                                        2 ...
                                                                                                          3
                                                                                                                 5
          0
              47 Business
                           2464
                                     0
                                                   0
                                                        0
                                                               3
                                                                                 2
                                                                                        2 ...
                                                                                                          4
                                                                                                                 2
                                                                      0
          1
              15
                           2138
                                     0
                                                   0
                                                        0
                                                               3
                                                                      2
                                                                                 0
                                                                                        2 ...
                                                                                                  3
                                                                                                                 4
          2
                    Eco
                                                        0
                                                                                        3 ...
                                                                                                                 4
          3
              60
                    Eco
                            623
                                     0
                                                   0
                                                               3
                                                                      3
                                                                                                  0
                                                                                                          1
                                                               3
                                                                                                          2
              70
                            354
                                                                                 3
                                                                                        4 ...
                                                                                                                 4
         5 rows × 22 columns
In [74]: print(f"Number of Independent variables: {airline_data.shape[1] - 1}")
          Number of Independent variables: 21
          After applying one-hot encoding, our dataset now contains 21 distinct independent variables.
In [16]: irline_data.drop(columns = ['Class']), airline_data['Class'], test_size=0.20, stratify = airline_data[
In [17]: train length = X train.shape[0]
```

Length of train and test data are: 103589 25898

print('Length of train and test data are:', train_length , test_length)

test_length = X_test.shape[0]

```
In [18]: first_row_index_train = X_train.index[0]
    first_row_index_test = X_test.index[0]
    print("First row index of X_train:", first_row_index_train)
    print("First row index of X_test:", first_row_index_test)

First row index of X_train: 100897
    First row index of X_test: 42248

In [19]: if False:
        from sklearn.preprocessing import StandardScaler
        sc = StandardScaler()
        X_train = pd.DataFrame(sc.fit_transform(X_train), columns = X_train.columns, index = X_train.index
        X_test = pd.DataFrame(sc.transform(X_test), columns = X_test.columns, index = X_test.index)
        X_train
        X_test
        y_train
        y_test
```

```
In [20]: model = LogisticRegression(fit_intercept = True, solver='lbfgs', multi_class = 'ovr', penalty = None)
          # If the lbfgs throws an error, try to increase max iter (add max iter = 1000),
          # also try another algorithm e.g. newton-cg, scaling is also suggested
          # While using multiclass case do multi_class = 'ovr' or 'auto'; can also try other solvers
          # While doing regularization, use penalty = '12' and also C = 10.0 (need to try other values too)
         model.fit(X_train, y_train)
          # The following gives the mean accuracy on the given data and labels
         model.score(X_train, y_train)
          # This is the coefficient Beta_1, ..., Beta_7
         model.coef
          # This is the coefficient Beta 0
         model.intercept_
          /Users/saisrivishwanath/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_logistic.py:46
          9: ConvergenceWarning: lbfgs 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 (https://scikit-learn.org/stable/mod
         ules/preprocessing.html)
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-l
          earn.org/stable/modules/linear model.html#logistic-regression)
           n_iter_i = _check_optimize_result(
Out[201:
                          LogisticRegression
                                                              (https://scikit-
learn.org/1.4/modules/generated/sklearn.linear_model.Logistic
          LogisticRegression(multi_class='ovr', penalty=None)
Out[20]: 0.6613540047688461
Out[20]: array([[ 7.06618599e-03, 3.59464328e-04, -3.53678291e-01,
                  -2.32563587e-01, 2.25418444e-01, -6.13281292e-02,
                  -3.21558782e-01, 5.98794075e-01, 1.71754167e-01,
                  -1.13346578e-02, 1.87829651e-01, 5.55016852e-03,
                  -7.79037986e-02, 2.52659107e-02, -1.27858250e-01,
                  -2.07406354e-01, 2.85713124e-04, 5.30569338e-04,
                  -8.32660387e-02, -1.99670468e-01, -1.18377935e+00],
                 [-5.46208506e-03, -2.37738592e-04, 3.02639201e-01,
                   2.30067134e-01, -1.86035461e-01, 7.29788855e-02,
                   2.44674669e-01, -5.64196301e-01, -1.82597249e-01,
                  -2.58311224e-02, -1.69828827e-01, -3.49631502e-02,
                   5.10489913e-02, -2.19677234e-02, 8.99504737e-02,
                 1.52343154e-01, 1.39224076e-02, -4.65463905e-03, 7.70101745e-02, 2.34894810e-01, 1.06616277e+00], [-7.94939012e-03, -2.57515956e-04, 2.41853942e-01,
                   9.12872791e-02, -5.46284016e-02, -1.16168516e-01,
                  -1.39422164e-02, -2.05972778e-01, -1.33918537e-01,
                   8.39381893e-02, -1.26309727e-01, -4.45891261e-02,
                  -6.96195088e-02, -1.09611509e-01, -4.55815980e-02,
                  -5.70727350e-03, -4.03005765e-03, 4.04153490e-03,
                  -6.51561626e-02, -2.61528467e-01, 3.44138237e-01]])
```

Out[20]: array([-0.22603403, 0.17452295, -0.04058616])

```
In [21]: model_iter = LogisticRegression(fit_intercept = True, solver='lbfgs', multi_class = 'ovr', penalty = 1
         # If the lbfgs throws an error, try to increase max iter (add max iter = 1000),
          # also try another algorithm e.g. newton-cg, scaling is also suggested
         # While using multiclass case do multi_class = 'ovr' or 'auto'; can also try other solvers
         # While doing regularization, use penalty = '12' and also C = 10.0 (need to try other values too)
         model_iter.fit(X_train, y_train)
         # The following gives the mean accuracy on the given data and labels
         model_iter.score(X_train, y_train)
          # This is the coefficient Beta_1, ..., Beta_7
         model iter.coef
         # This is the coefficient Beta 0
         model_iter.intercept_
          /Users/saisrivishwanath/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_logistic.py:46
         9: ConvergenceWarning: lbfgs 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 (https://scikit-learn.org/stable/mod
         ules/preprocessing.html)
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-l
         earn.org/stable/modules/linear model.html#logistic-regression)
           n_iter_i = _check_optimize_result(
Out[21]:
                                  LogisticRegression
                                                                             (https://scikit-
                                                                               arn.org/1.4/modules/generated/sklearn.lin
          LogisticRegression(max iter=1000, multi class='ovr', penalty=None)
Out[21]: 0.7673112009962447
Out[21]: array([[-3.20544596e-03, 2.17897686e-04, -4.08103418e-01,
                   4.15611893e-02, 7.41467636e-02, -4.18019239e-02,
                  -3.72437807e-02, 3.39228432e-01, 1.95902178e-01,
                  -3.03358588e-01, 2.51072076e-01, 4.81433162e-02,
                  1.82415292e-01, 1.47444176e-01, 1.78761309e-01,
                   4.00755645e-02, 3.92770098e-03, -5.85087532e-03,
                  -3.44121927e-02, -1.62265684e+00, -4.32528932e+00],
                 [ 1.51520741e-04, -1.94598452e-04, 3.68306744e-01,
                  -3.26420544e-02, -9.90425806e-02, 2.89366887e-03,
                  1.70828405e-02, -2.64331254e-01, -1.63407576e-01,
                  1.78121292e-01, -1.77902065e-01, -4.94488842e-02,
                  -1.41790825e-01, -1.32873861e-01, -1.33670109e-01,
                 -1.00859933e-02, -2.47638718e-03, 3.98521404e-03, 1.02789525e-02, 1.77441182e+00, 3.45438133e+00], [-6.85082518e-03, -2.09362812e-04, 1.87038241e-01,
                   5.94600701e-03, -2.61237578e-02, -6.47455302e-02,
                   1.16596592e-03, -1.82800791e-01, -1.13152274e-01,
                   8.56195063e-02, -1.37853467e-01, -6.72078522e-02,
                  -7.10646654e-02, -1.01834992e-01, -5.33867619e-02,
                  -2.87469077e-03, -2.78219355e-03, 2.91073454e-03,
                  -1.71530401e-01, -6.29347993e-01, 6.31136916e-01]])
Out[21]: array([-1.61202502, 1.04020571, -0.09113751])
In [22]: from sklearn.preprocessing import StandardScaler
         sc = StandardScaler()
         X_train_scaled = pd.DataFrame(sc.fit_transform(X_train), columns = X_train.columns, index = X_train.in
         X test scaled = pd.DataFrame(sc.transform(X test), columns = X test.columns, index = X test.index)
```

```
In [23]: model.fit(X_train_scaled, y_train)
          # The following gives the mean accuracy on the given data and labels
          model.score(X_train_scaled, y_train)
          # This is the coefficient Beta 1, ..., Beta 7
          model.coef_
          # This is the coefficient Beta 0
          model.intercept_
Out[23]:
                           LogisticRegression
                                                                (https://scikit-
                                                                learn.org/1.4/modules/generated/sklearn.linear model.Logistic
          LogisticRegression(multi_class='ovr', penalty=None)
Out[23]: 0.7722538107327999
Out[23]: array([[ 1.92350151e-01, 3.98843275e-01, -7.48912432e-01,
                   7.38734817e-02, 2.24779006e-01, 3.63847633e-02,
                   5.92900411e-02, 5.73412810e-01, 3.13650234e-01,
                  -3.81258474e-01, 3.51603750e-01, 1.21784845e-01,
                   2.93748295e-01, 2.64173994e-01, 2.66793956e-01,
                   1.51422229e-02, 1.05983253e-01, -1.67093697e-01,
                   2.44247769e-02, -5.20854523e-01, -2.01951663e+00],
                 [-1.23328479e-01, -3.00680892e-01, 4.94654072e-01,
                  -3.00284129e-02, -1.69629613e-01, -3.01794344e-02,
                  -5.13443440e-02, -3.71721706e-01, -2.14756365e-01,
                   2.84019325e-01, -2.30218397e-01, -9.80804454e-02,
                  -2.05483289e-01, \ -1.86622955e-01, \ -1.98943371e-01,
                  -2.87800670e-02, -6.43083629e-02, 1.16245397e-01,
                 -1.69963887e-02, 6.18625698e-01, 1.50362227e+00], [-1.01247359e-01, -2.05972879e-01, 2.72977991e-01,
                   2.16801420e-03, -5.29509488e-02, -6.50657223e-02,
                   1.02114691e-03, -2.59700973e-01, -1.38714436e-01,
                   8.92977164e-02, -1.74585465e-01, -8.51611230e-02,
                  -7.38948697e-02, -1.19994639e-01, -4.79272505e-02,
                   9.62358055e-03, -9.59894123e-02, 1.04923402e-01, -8.25213022e-02, -2.93844235e-01, 2.60194444e-01]])
```

Out[23]: array([-0.28500927, -0.3125446 , -2.73450827])

```
In [24]: model_newton_cg = LogisticRegression(fit_intercept = True, solver='newton-cg', multi_class = 'ovr')
         # If the lbfgs throws an error, try to increase max iter (add max iter = 1000),
          # also try another algorithm e.g. newton-cg, scaling is also suggested
         # While using multiclass case do multi_class = 'ovr' or 'auto'; can also try other solvers
         # While doing regularization, use penalty = '12' and also C = 10.0 (need to try other values too)
         model_newton_cg.fit(X_train, y_train)
         # The following gives the mean accuracy on the given data and labels
         model_newton_cg.score(X_train, y_train)
         # This is the coefficient Beta_1, ..., Beta_7
         model_newton_cg.coef_
         # This is the coefficient Beta 0
         model_newton_cg.intercept_
Out[24]:
                             LogisticRegression
                                                                   (https://scikit-
                                                                    learn.org/1.4/modules/generated/sklearn.linear_model.L
          LogisticRegression(multi_class='ovr', solver='newton-cg')
Out[24]: 0.7722055430595912
Out[24]: array([[ 1.26970813e-02, 3.87879520e-04, -5.37495775e-01,
                   4.79139266e-02, 1.56381885e-01, 2.78761314e-02,
                   4.44767090e-02, 4.25722659e-01, 2.40018833e-01,
                  -2.91765618e-01, 2.76361799e-01, 9.43642403e-02,
                   2.54323406e-01, 2.09683933e-01, 2.31664563e-01,
                   1.19277340e-02, 2.77612470e-03, -4.31601697e-03,
                   4.90897425e-02, -1.34515316e+00, -4.36559225e+00],
                 [-8.16212981e-03, -2.92738023e-04, 3.55154602e-01,
                  -1.93731287e-02, -1.18153903e-01, -2.30727594e-02,
                 -3.85707786e-02, -2.75948555e-01, -1.64222930e-01,
                  2.16977949e-01, -1.80761345e-01, -7.57810036e-02,
                 -1.78148403e-01, -1.48265470e-01, -1.72938455e-01,
                 -2.23957802e-02, -1.66308875e-03, 2.98434772e-03,
                -3.38747270e-02, 1.59717904e+00, 3.25196339e+00], [-6.77108986e-03, -2.01876730e-04, 1.93620199e-01,
                   8.96019369e-04, -3.39283364e-02, -5.08758138e-02,
                   2.18657950e-03, -1.93620109e-01, -1.07748333e-01,
                   6.80841926e-02, -1.37714778e-01, -6.62769803e-02,
                  -6.38382228e-02, -9.50353114e-02, -4.16377542e-02,
                  7.74502901e-03, -2.64519856e-03, 2.82099990e-03,
                  -1.65730292e-01, -7.66194963e-01, 5.61290038e-01]])
Out[24]: array([-4.34712091, 2.38750854, -0.14531157])
In [25]: test_output_iter = pd.DataFrame(model_iter.predict(X_test_scaled), index = X_test_scaled.index, column
         test_output_iter.head()
Out[25]:
                pred_class
           42248
          102458
                  Business
```

236

74922

14632

Eco

Eco

Business

Percentage of correct predictions is 0.7439956753417253

Eco

Business Business

Eco

In [27]: test_output = pd.DataFrame(model.predict(X_test_scaled), index = X_test_scaled.index, columns = ['predict_scaled]

Out[27]:

	pred_class
42248	Eco
102458	Business
236	Eco
74922	Business
14632	Fco

74922

14632

```
In [28]: test_output = test_output.merge(y_test, left_index = True, right_index = True)
    test_output.head()
    print('Percentage of correct predictions is ')
    print(model.score(X_test_scaled, y_test))
```

Out[28]:

	pred_class	Class
42248	Eco	Business
102458	Business	Business
236	Eco	Eco
74922	Business	Business
14632	Eco	Eco

Percentage of correct predictions is 0.775040543671326

Out[29]:

	pred_class
42248	Eco
102458	Business
236	Eco
74922	Eco Plus
14632	Eco

```
In [30]: | test_output_newton_cg = test_output_newton_cg.merge(y_test, left_index = True, right_index = True)
         test output newton cg.head()
         print('Percentage of correct predictions is ')
         print(model_newton_cg.score(X_test_scaled, y_test))
Out[30]:
                pred_class
                           Class
                     Eco Business
           42248
                  Business Business
          102458
                     Eco
                             Eco
            236
                  Eco Plus Business
           74922
           14632
                     Eco
                             Fco
          Percentage of correct predictions is
          0.6044482199397637
In [31]: from sklearn.metrics import confusion matrix
         y_true = test_output['Class'] # Actual class labels
         y_pred = test_output['pred_class'] # Predicted class labels by your model
         # Generating the confusion matrix
         cm = confusion_matrix(y_true, y_pred, labels=np.unique(y_true))
         # Calculate the number of incorrect predictions for each class
         wrong_predictions = cm.sum(axis=1) - np.diag(cm)
          # Convert wrong predictions to a Series for easier handling, assuming 'np.unique(y true)' gives the c
         wrong_predictions_series = pd.Series(wrong_predictions, index=np.unique(y_true))
         # Find the class with the most and least wrong predictions
         most_wrong_class = wrong_predictions_series.idxmax()
         least_wrong_class = wrong_predictions_series.idxmin()
         print(f"Class predicted wrong the most: {most_wrong_class}")
         print(f"Class predicted wrong the least: {least_wrong_class}")
         Class predicted wrong the most: Eco
         Class predicted wrong the least: Business
         K-NN
In [66]: from sklearn.neighbors import KNeighborsClassifier
          # Assuming X train scaled and y train are correctly defined and not None
         knn = KNeighborsClassifier(n neighbors=7)
         knn.fit(X_train_scaled, y_train)
Out[66]:
                 KNeighborsClassifier
                                            (https://scikit-
                                             earn.org/1.4/modules/generated/sklearn.neighbors.KNeighborsClassifier.html)
         KNeighborsClassifier(n_neighbors=7)
In [67]: # Check the score on the train data to ensure it's correctly fitted
         train_score = knn.score(X_train_scaled.to_numpy(), y_train)
         print("Score (fraction of accurate predictions) on the train data:", train_score)
```

/Users/saisrivishwanath/anaconda3/lib/python3.11/site-packages/sklearn/base.py:493: UserWarning: X does not have valid feature names, but KNeighborsClassifier was fitted with feature names warnings.warn(

Score (fraction of accurate predictions) on the train data: 0.8566063964320536

In [68]: test_output_knn = pd.DataFrame(knn.predict(X_test_scaled.to_numpy()), index = X_test_scaled.index, col
test_output_knn.head()

/Users/saisrivishwanath/anaconda3/lib/python3.11/site-packages/sklearn/base.py:493: UserWarning: X does not have valid feature names, but KNeighborsClassifier was fitted with feature names warnings.warn(

Out[68]:

	pred_class
42248	Eco
102458	Business
236	Eco
74922	Business
14632	Eco

In [69]: test_output_knn = test_output_knn.merge(y_test, left_index = True, right_index = True)
 test_output_knn.head()

Out[69]:

	pred_class	Class
42248	Eco	Business
102458	Business	Business
236	Eco	Eco
74922	Business	Business
14632	Eco	Eco

```
In [71]: print('Percentage of correct predictions is ')
   print(knn.score(X_test_scaled.to_numpy(), y_test))
```

Percentage of correct predictions is

/Users/saisrivishwanath/anaconda3/lib/python3.11/site-packages/sklearn/base.py:493: UserWarning: X does not have valid feature names, but KNeighborsClassifier was fitted with feature names warnings.warn(

0.8285581898216079

Multinomial Logistic Regression with Penalty

```
In [77]: airline_data2 = pd.read_csv('Invistico_Airline.csv')
airline_data2.head()
```

Out[77]:

	satisfaction	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Seat comfort	Departure/Arrival time convenient	Food and drink	 Online support	Ease of Online booking	On- board service	5
0	satisfied	Female	Loyal Customer	65	Personal Travel	Eco	265	0	0	0	 2	3	3	
1	satisfied	Male	Loyal Customer	47	Personal Travel	Business	2464	0	0	0	 2	3	4	
2	satisfied	Female	Loyal Customer	15	Personal Travel	Eco	2138	0	0	0	 2	2	3	
3	satisfied	Female	Loyal Customer	60	Personal Travel	Eco	623	0	0	0	 3	1	1	
4	satisfied	Female	Loyal Customer	70	Personal Travel	Eco	354	0	0	0	 4	2	2	

5 rows × 23 columns

```
In [78]: print("The column names in the dataframe are")
         list(airline_data2.columns)
         The column names in the dataframe are
Out[78]: ['satisfaction',
          'Gender',
          'Customer Type',
          'Age',
          'Type of Travel',
          'Class',
          'Flight Distance',
          'Seat comfort',
          'Departure/Arrival time convenient',
          'Food and drink',
          'Gate location',
          'Inflight wifi service',
          'Inflight entertainment',
          'Online support',
          'Ease of Online booking',
          'On-board service',
          'Leg room service',
          'Baggage handling',
          'Checkin service',
          'Cleanliness',
          'Online boarding',
          'Departure Delay in Minutes',
           'Arrival Delay in Minutes']
In [79]: airline_data2.isna().sum()
Out[79]: satisfaction
                                                 0
         Gender
                                                 0
                                                 0
         Customer Type
         Age
         Type of Travel
                                                 0
                                                 0
         Class
         Flight Distance
                                                 0
         Seat comfort
                                                 0
         Departure/Arrival time convenient
                                                 0
         Food and drink
                                                 0
         Gate location
         Inflight wifi service
                                                 0
         Inflight entertainment
                                                 n
         Online support
                                                 0
         Ease of Online booking
                                                 0
         On-board service
                                                 0
         Leg room service
                                                 0
         Baggage handling
         Checkin service
                                                 0
         Cleanliness
                                                 0
         Online boarding
                                                 0
         Departure Delay in Minutes
                                                 0
         Arrival Delay in Minutes
                                               393
         dtype: int64
```

```
In [87]: airline data2 = airline data2.dropna()
           airline_data2.head()
Out[87]:
                                                                                                                              On-
                                                                                                  Food
                                                                                                                   Ease of
                                                 Type of
                                 Customer
                                                                   Flight
                                                                            Seat Departure/Arrival
                                                                                                           Online
              satisfaction Gender
                                           Age
                                                           Class
                                                                                                  and
                                                                                                                    Online
                                                                                                                            board
                                                                 Distance comfort
                                     Type
                                                  Travel
                                                                                   time convenient
                                                                                                          support
                                                                                                 drink
                                                                                                                  booking
                                                                                                                           service
                                     Loyal
                                                Personal
           0
                 satisfied
                         Female
                                            65
                                                            Eco
                                                                     265
                                                                               0
                                                                                               n
                                                                                                     0
                                                                                                                2
                                                                                                                        3
                                                                                                                                3
                                  Customer
                                                  Travel
                                     Loyal
                                                Personal
                  satisfied
                                            47
                                                                    2464
                                                                               0
                                                                                                     0 ...
                                                                                                                2
                                                                                                                        3
            1
                            Male
                                                        Business
                                                                                                                                4
                                  Customer
                                                  Travel
                                     Loyal
                                                Personal
           2
                  satisfied
                         Female
                                            15
                                                            Eco
                                                                    2138
                                                                               0
                                                                                               O
                                                                                                     0 ...
                                                                                                                2
                                                                                                                        2
                                                                                                                                3
                                  Customer
                                                  Travel
                                                Personal
                                     Loyal
                                                                                                     0 ...
           3
                                            60
                                                                     623
                                                                               0
                                                                                               0
                                                                                                                        1
                  satisfied
                         Female
                                                            Eco
                                                                                                                3
                                                                                                                                1
                                  Customer
                                                  Travel
                                     Loyal
                                                Personal
                                            70
                                                                     354
                                                                               0
                                                                                               0
                                                                                                     0 ...
                                                                                                                4
                                                                                                                        2
                                                                                                                               2
                 satisfied
                         Female
                                                            Eco
                                  Customer
                                                  Travel
           5 rows × 23 columns
In [88]: filtered airline data = airline data2[airline data2['Inflight entertainment'] == 0]
In [89]: filtered_airline_data.shape
Out[89]: (2968, 23)
In [90]: X = filtered_airline_data.drop(columns=['satisfaction', 'Class', 'Inflight entertainment'])
           y = filtered airline data['Class']
In [91]: from sklearn.preprocessing import OneHotEncoder
           def get ohe(df, col):
                ohe = OneHotEncoder(drop='first', handle_unknown='error', sparse_output=False, dtype='int')
                ohe.fit(df[[col]])
                temp_df = pd.DataFrame(data=ohe.transform(df[[col]]), columns=ohe.get_feature_names_out())
                # If you have a newer version, replace with columns=ohe.get_feature names_out()
                df.drop(columns=[col], axis=1, inplace=True)
                df = pd.concat([df.reset index(drop=True), temp df], axis=1)
In [92]: X = get_ohe(X, 'Gender')
           X = get_ohe(X, 'Customer Type')
           X = get_ohe(X, 'Type of Travel')
In [93]: X.head()
Out[93]:
                                                                  Inflight
                                                                                  Ease of
                                                                                             On-
                                                    Food
                                                                                                    Leg
                      Flight
                               Seat Departure/Arrival
                                                             Gate
                                                                           Online
                                                                                                         Baggage
                                                                                                                  Checkin
                                                                                                                          Cleanlines
                                                     and
                                                                     wifi
                                                                                   Online
                                                                                           board
                                                                                                   room
              Age
                   Distance
                            comfort
                                     time convenient
                                                          location
                                                                          support
                                                                                                         handling
                                                                                                                   service
                                                    drink
                                                                                  booking
                                                                  service
                                                                                          service
                                                                                                 service
           0
                15
                       2138
                                  0
                                                 0
                                                       0
                                                               3
                                                                       2
                                                                                                                        4
                                                                                               3
                                                                                                      3
                30
                                  0
                                                 0
                                                       0
                                                               3
                                                                       2
                                                                               2
                                                                                       2
                                                                                               5
                                                                                                      4
                                                                                                               5
                                                                                                                        5
           1
                       1894
           2
                10
                       1812
                                  0
                                                 0
                                                       0
                                                               3
                                                                       2
                                                                               2
                                                                                       2
                                                                                               3
                                                                                                                        5
                                                                               2
            3
               22
                       1556
                                  O
                                                 0
                                                       0
                                                               3
                                                                       2
                                                                                       2
                                                                                               2
                                                                                                               5
                                                                                                                        3
            4
                34
                       3633
                                                 0
                                                                       2
                                                                               2
                                                                                                                        2
```

```
In [52]: X_train2, X_test2, y_train2, y_test2 = train_test_split(X, y, test_size=0.2, random_state=50, stratif
```

```
In [53]: from sklearn.preprocessing import StandardScaler
    sc = StandardScaler()
    X_train_scaled2 = pd.DataFrame(sc.fit_transform(X_train2), columns = X_train2.columns, index = X_train2.columns, index = X_train2.columns, index = X_train2.columns, index = X_test2.index
```

```
In [56]:
          model = LogisticRegression(fit intercept = True, multi class='ovr', solver='lbfgs', penalty=None)
          # Fit the model on the training data
          model.fit(X_train_scaled2, y_train2)
          train_score = model.score(X_train_scaled2, y_train2)
          test_score = model.score(X_test_scaled2, y_test2)
          train score percentage = "{:.2f}".format(train score * 100)
          test_score_percentage = "{:.2f}".format(test_score * 100)
          print(f"Accuracy for train dataset is: {train_score_percentage} %")
          print(f"Accuracy value for test dataset is: {test_score_percentage} %")
          # This is the coefficient Beta_1, ..., Beta_7
          model.coef
          # This is the coefficient Beta 0
          model.intercept_
Out[56]:
                            LogisticRegression
                                                                  (https://scikit-
                                                                  learn.org/1.4/modules/generated/sklearn.linear model.Logistic
          LogisticRegression(multi_class='ovr', penalty=None)
          Accuracy for train dataset is: 78.10 %
          Accuracy value for test dataset is: 75.76 %
Out[56]: array([[-0.47621213, 0.50458457, -0.06448408, -0.33471057, 0.0214228,
                    0.136524 \quad , \quad -0.02677323 \, , \quad 0.08269893 \, , \quad -0.02677323 \, , \quad 0.19339392 \, ,
                    0.18297614, \quad 0.44785498, \quad 0.17571178, \quad 0.3999089 \ , \ -0.02677323,
                  -0.17356831, 0.24310981, 0.05412453, 0.83162775, -0.61930582], [ 0.11940852, -0.26717072, 0.09330552, 0.24956706, -0.03542464, 0.0216197, 0.00890864, 0.0291108, 0.00890864, -0.17001247,
                   -0.09845438, \ -0.24200546, \ -0.14589332, \ -0.23354806, \ \ 0.00890864,
                    0.08068188, \ -0.06336826, \ -0.02415577, \ \ 0.07606072, \ \ 0.92910376],
                   [ \ 0.10242211, \ -0.039159 \ , \ -0.06795014, \ \ 0.05612588, \ -0.75621926, 
                   -0.22784554, \quad 0.02064203, \ -0.15553278, \quad 0.02064203, \quad 0.00927705,
                   Out[56]: array([-2.23536051, 0.9030872, -2.52839323])
```

```
In [62]: model 11 = LogisticRegression(penalty='11', solver='liblinear', multi class='ovr', C=0.1)
         model_l1.fit(X_train_scaled2, y_train2)
          # Prediction accuracy on the train set
         train_score_l1 = model_l1.score(X_train_scaled2, y_train2)
          test_score_l1 = model_l1.score(X_test_scaled2, y_test2)
          train_score_percentage = "{:.2f}".format(train_score_l1 * 100)
         test_score_percentage = "{:.2f}".format(test_score_l1 * 100)
         print(f"Accuracy for train dataset is: {train score percentage} %")
         print(f"Accuracy value for test dataset is: {test_score_percentage} %")
          zero_coef_features = X.columns[model_l1.coef_[0] == 0]
          print("Features with nearly zero coefficients:", zero_coef_features)
         model 11.coef
          # This is the coefficient Beta 0
         model_l1.intercept_
Out[62]:
                                         LogisticRegression
                                                                                           (https://scikit-
                                                                                            learn.org/1.4/modules/generat
          LogisticRegression(C=0.1, multi_class='ovr', penalty='l1', solver='liblinear')
          Accuracy for train dataset is: 77.72 %
          Accuracy value for test dataset is: 76.43 %
          Features with nearly zero coefficients: Index(['Seat comfort', 'Food and drink', 'Inflight wifi ser
          vice',
                 'Online support', 'Ease of Online booking', 'Online boarding',
                 'Departure Delay in Minutes'],
                dtype='object')
Out[62]: array([[-3.48356738e-01, 4.35148646e-01, 0.00000000e+00,
                  -2.88405619e-01, 0.00000000e+00, 8.80878226e-02,
                   0.00000000e+00, 0.0000000e+00, 0.0000000e+00,
                   1.66916622e-01, 1.29700825e-01, 3.99481456e-01,
                   1.41960669e-01, 3.55776677e-01, 0.00000000e+00, 0.00000000e+00, 3.44781956e-02, 8.31561231e-03,
                   8.10662286e-01, -5.50525731e-01],
                 [ 9.04868864e-02, -2.50370437e-01, 4.58425743e-02,
                   2.17907123e-01, 0.00000000e+00, 5.28911494e-04,
                   9.52651053e-04, 2.71648086e-02, 0.00000000e+00,
                  -1.46924470e-01, -6.77918105e-02, -2.13672811e-01,
                  -1.26786032e-01, -2.07496390e-01, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 8.61618742e-01], [ 3.16979174e-02, 0.00000000e+00, -6.30113595e-02,
                   0.00000000e+00, 0.0000000e+00, -1.67040835e-01,
                   0.00000000e+00, -5.90886668e-02, 0.00000000e+00,
                   0.0000000e+00, 0.0000000e+00, -3.63435038e-02,
                   0.00000000e+00, -2.82015694e-03, 0.0000000e+00,
                  -6.60716810e-03, -5.53199834e-02, 0.00000000e+00,
                  -1.18590764e+00, -7.30746770e-01]])
Out[62]: array([-2.01967673, 0.84974865, -2.28844403])
```

The accuracy of both the test and train datasets remains similar to that of the prior model, showing little to no improvement.

```
In [63]: model 12 = LogisticRegression(penalty='12', solver='liblinear', multi class='ovr', C=0.1)
           model_12.fit(X_train_scaled2, y_train2)
           # Prediction accuracy on the train set
           train_score_12 = model_12.score(X_train_scaled2, y_train2)
           test_score_12 = model_12.score(X_test_scaled2, y_test2)
           train_score_percentage = "{:.2f}".format(train_score_12 * 100)
           test_score_percentage = "{:.2f}".format(test_score_12 * 100)
           print(f"Accuracy for train dataset is: {train_score_percentage} %")
           print(f"Accuracy value for test dataset is: {test_score_percentage} %")
           zero_coef_features = X.columns[model_12.coef_[0] == 0]
           print("Features with nearly zero coefficients:", zero_coef_features)
           model 12.coef
           # This is the coefficient Beta 0
           model_12.intercept_
Out[63]:
                                      LogisticRegression
                                                                                      (https://scikit-
learn.org/1.4/modules/generated/sklearn.linear
           LogisticRegression(C=0.1, multi_class='ovr', solver='liblinear')
           Accuracy for train dataset is: 78.14 %
           Accuracy value for test dataset is: 76.26 %
           Features with nearly zero coefficients: Index([], dtype='object')
Out[63]: array([[-0.38252057, 0.44361472, -0.07361526, -0.32634472, 0.03287364,
                     0.12495599, \; -0.02299086, \quad 0.06673279, \; -0.02299086, \quad 0.18940882,
                   0.16436397, 0.41089333, 0.16568819, 0.36659023, -0.02299086, -0.08634753, 0.15032678, 0.04914887, 0.77692149, -0.5352716], [ 0.12065161, -0.26105232, 0.1018327, 0.25260082, -0.03925346,
                     0.02070732, 0.00786924, 0.03089209, 0.00786924, -0.1642268,
                    -0.09309192, \; -0.22982241, \; -0.1401279 \;\;, \; -0.22075727, \quad 0.00786924,
                     0.06192805, -0.04712102, -0.0233684, 0.03423618, 0.85764125],
                    [ \ 0.08098705, \ -0.01948679, \ -0.07991317, \ \ 0.03393322, \ -0.13813498, 
                    -0.19504592, 0.01616941, -0.12862822, 0.01616941, 0.00424908, -0.01175292, -0.06820488, 0.02646627, -0.03935987, 0.01616941, -0.02735243, -0.07798507, -0.03641305, -1.10915329, -0.74178725]])
Out[63]: array([-1.99740698, 0.86650215, -2.23776556])
 In [ ]:
```