```
!pip install pandas
!pip install numpy
!pip install matplotlib
!pip install seaborn
!pip install sklearn
```

```
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (2.2.2)
Requirement already satisfied: numpy>=1.22.4 in /usr/local/lib/python3.10/dist-packages (from pandas) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas) (2024.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.2->pandas) (1.16.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (1.26.4)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (3.8.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.3.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (4.54.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.7)
Requirement already satisfied: numpy<2,>=1.21 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.26.4)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (24.1)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (10.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (3.2.0)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib) (1.16.0)
Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-packages (0.13.2)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in /usr/local/lib/python3.10/dist-packages (from seaborn) (1.26.4)
Requirement already satisfied: pandas>=1.2 in /usr/local/lib/python3.10/dist-packages (from seaborn) (2.2.2)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in /usr/local/lib/python3.10/dist-packages (from seaborn) (3.8.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (1.3.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (4.54.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (1.4.7)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (24.1)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (10.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (3.2.0)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.2->seaborn) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.2->seaborn) (2024.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>=3.4->seaborn) (1.16
Collecting sklearn
  Using cached sklearn-0.0.post12.tar.gz (2.6 kB)
  error: subprocess-exited-with-error

  × python setup.py egg_info did not run successfully.
  │ exit code: 1
  ╰─> See above for output.

  note: This error originates from a subprocess, and is likely not a problem with pip.
  Preparing metadata (setup.py) ... error
error: metadata-generation-failed

× Encountered error while generating package metadata.
╰─> See above for output.

note: This is an issue with the package mentioned above, not pip.
hint: See above for details.
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from google.colab import files
uploaded = files.upload()
in_vehicle_coupon_data = pd.read_csv("in-vehicle-coupon-recommendation.csv")
in_vehicle_coupon_data.head() #Display the first few rows
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving in-vehicle-coupon-recommendation.csv to in-vehicle-coupon-recommendation (2).csv
```

	destination	passanger	weather	temperature	time	coupon	expiration	gender	age	maritalStatus	...	CoffeeHouse	CarryAway	RestaurantLe
0	No Urgent Place	Alone	Sunny	55	2PM	Restaurant(<20)	1d	Female	21	Unmarried partner	...	never	NaN	
1	No Urgent Place	Friend(s)	Sunny	80	10AM	Coffee House	2h	Female	21	Unmarried partner	...	never	NaN	
2	No Urgent Place	Friend(s)	Sunny	80	10AM	Carry out & Take away	2h	Female	21	Unmarried partner	...	never	NaN	
3	No Urgent Place	Friend(s)	Sunny	80	2PM	Coffee House	2h	Female	21	Unmarried partner	...	never	NaN	
4	No Urgent Place	Friend(s)	Sunny	80	2PM	Coffee House	1d	Female	21	Unmarried partner	...	never	NaN	

5 rows × 26 columns

```
in_vehicle_coupon_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12684 entries, 0 to 12683
Data columns (total 26 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   destination           12684 non-null  object
 1   passanger             12684 non-null  object
 2   weather               12684 non-null  object
 3   temperature           12684 non-null  int64
 4   time                  12684 non-null  object
 5   coupon                12684 non-null  object
 6   expiration            12684 non-null  object
 7   gender                12684 non-null  object
 8   age                   12684 non-null  object
 9   maritalStatus         12684 non-null  object
 10  has_children          12684 non-null  int64
 11  education             12684 non-null  object
 12  occupation            12684 non-null  object
 13  income                12684 non-null  object
 14  car                   108 non-null    object
 15  Bar                   12577 non-null  object
 16  CoffeeHouse           12467 non-null  object
 17  CarryAway             12533 non-null  object
 18  RestaurantLessThan20  12554 non-null  object
 19  Restaurant20To50      12495 non-null  object
 20  toCoupon_GEQ5min      12684 non-null  int64
 21  toCoupon_GEQ15min     12684 non-null  int64
 22  toCoupon_GEQ25min     12684 non-null  int64
 23  direction_same        12684 non-null  int64
 24  direction_opp         12684 non-null  int64
 25  Y                     12684 non-null  int64
dtypes: int64(8), object(18)
memory usage: 2.5+ MB
```

```
#This code snippet has been taken from Niralidedaniya (2022).
print('Is there any missing value present or not?',in_vehicle_coupon_data.isnull().values.any())
missing_percentage = in_vehicle_coupon_data.isnull().sum()*100/len(in_vehicle_coupon_data) #Calculate the percentage of missing data
missing_value_df = pd.DataFrame({'missing_count': in_vehicle_coupon_data.isnull().sum(),'missing_percentage': missing_percentage}) #create a dataframe
print(missing_value_df) #print the dataframe created in the previous step
```

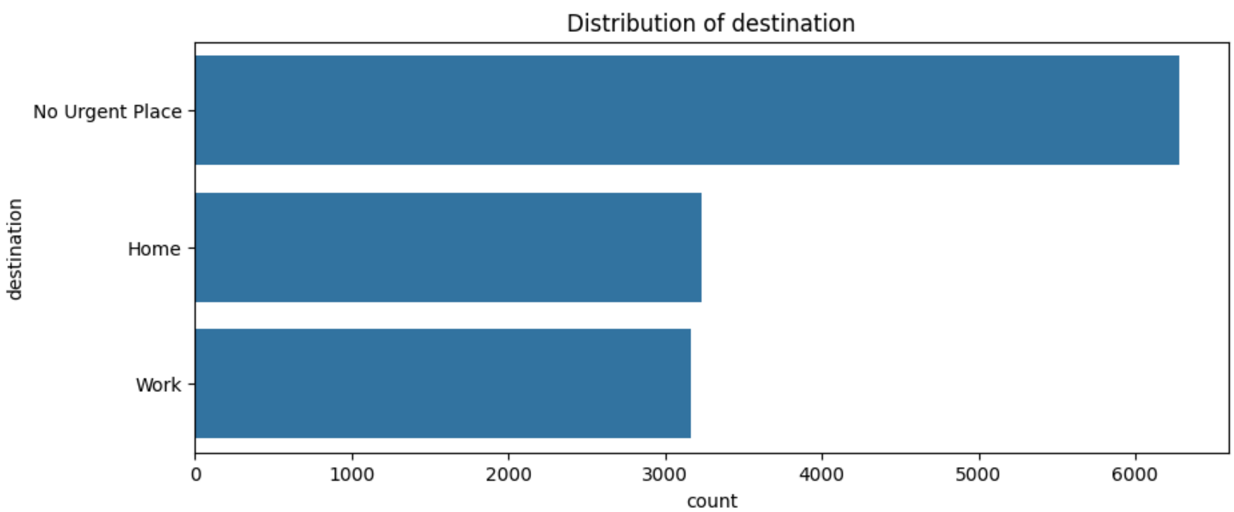
```
Is there any missing value present or not? True
                      missing_count  missing_percentage
destination                       0            0.000000
passanger                         0            0.000000
weather                           0            0.000000
temperature                       0            0.000000
time                              0            0.000000
coupon                            0            0.000000
expiration                        0            0.000000
gender                            0            0.000000
age                               0            0.000000
maritalStatus                     0            0.000000
has_children                      0            0.000000
education                         0            0.000000
occupation                        0            0.000000
income                            0            0.000000
car                           12576           99.148534
Bar                             107            0.843582
CoffeeHouse                     217            1.710817
CarryAway                       151            1.190476
```

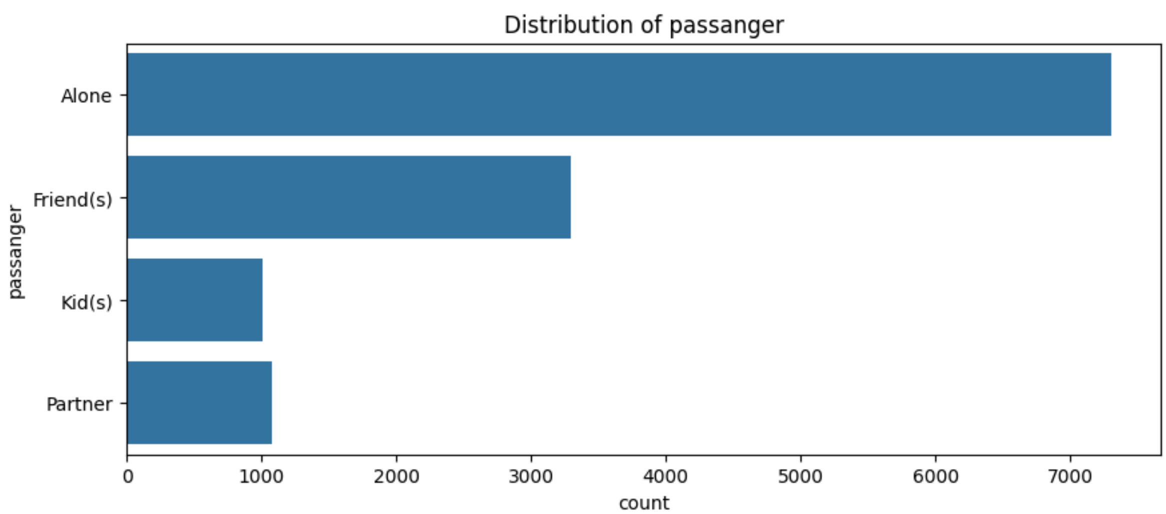
```
RestaurantLessThan20          130          1.024913
Restaurant20To50              189          1.490066
toCoupon_GEQ5min                0          0.000000
toCoupon_GEQ15min               0          0.000000
toCoupon_GEQ25min               0          0.000000
direction_same                  0          0.000000
direction_opp                   0          0.000000
Y                               0          0.000000
```

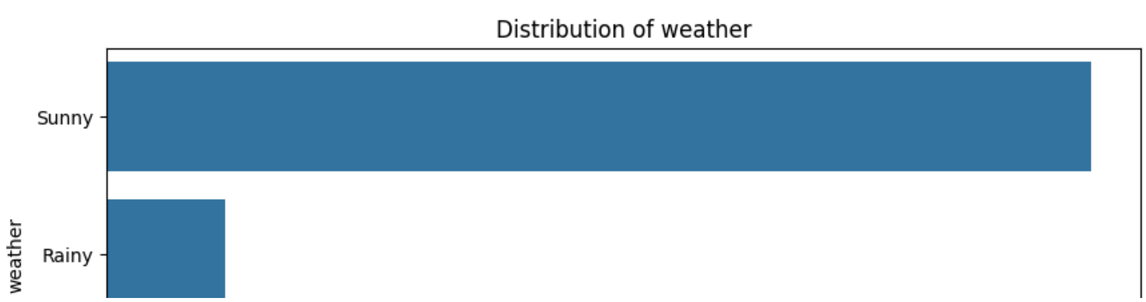
```
#This code snippet has been taken from Niralidedaniya (2022).
#For the target column, calculate the percentage of coupons accepted and rejected.
Y_counts = in_vehicle_coupon_data.groupby('Y').Y.count()
print('Accepted coupons:',Y_counts[1],round(Y_counts[1]/in_vehicle_coupon_data.shape[0]*100,3),'%')
print('Rejected coupons:',Y_counts[0],round(Y_counts[0]/in_vehicle_coupon_data.shape[0]*100,3),'%')
```

```
Accepted coupons: 7210 56.843 %
Rejected coupons: 5474 43.157 %
```

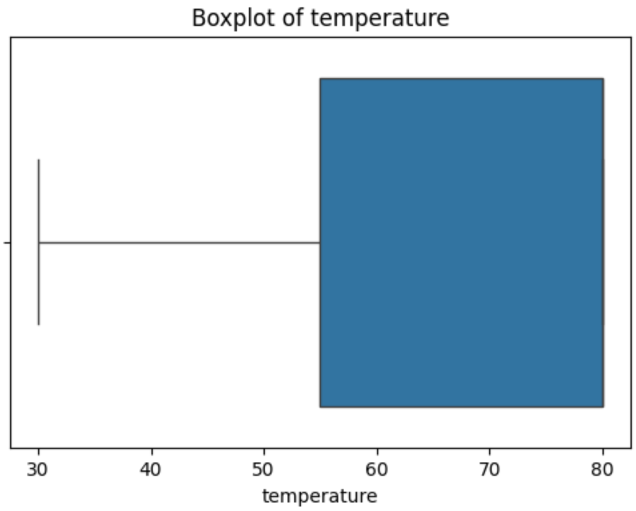
```
#This code snippet came from Inyama (2023).
#We want to see the distribution of data in each of the columns that have categorical data
categorical_variables = in_vehicle_coupon_data.select_dtypes(include=['object']).columns
for var in categorical_variables:
    plt.figure(figsize=(10, 4))
    sns.countplot(y=var, data=in_vehicle_coupon_data)
    plt.title(f'Distribution of {var}')
    plt.show()
```

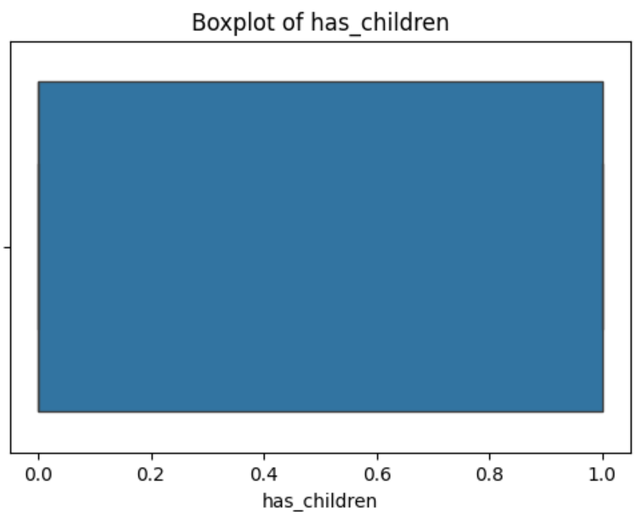


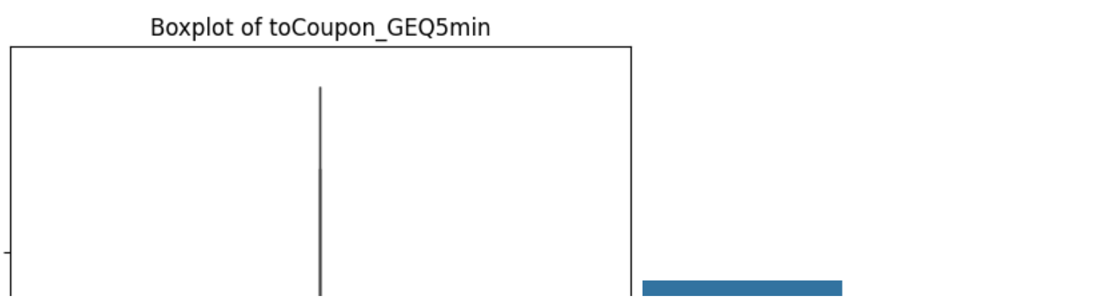




```
#This code snippet came from Inyama (2023).
#We want to see the box plot for numerical data in numerical columns
numerical_columns = in_vehicle_coupon_data.select_dtypes(include=['int64', 'float64']).columns.tolist()
numerical_columns.remove('Y')
for column in numerical_columns:
    plt.figure(figsize=(6, 4))
    sns.boxplot(x=in_vehicle_coupon_data[column])
    plt.title(f'Boxplot of {column}')
    plt.show()
```








```
#Drop column car as it has too many missing values
#Drop column toCoupon_GEQ5min because there is no variability in its value
#Drop column occupation because it has too many categories that leads to a lot of noise
in_vehicle_coupon_data = in_vehicle_coupon_data.drop(['car', 'occupation', 'toCoupon_GEQ5min'], axis=1)
in_vehicle_coupon_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12684 entries, 0 to 12683
Data columns (total 23 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   destination           12684 non-null  object
 1   passanger             12684 non-null  object
 2   weather               12684 non-null  object
 3   temperature           12684 non-null  int64
 4   time                  12684 non-null  object
 5   coupon                12684 non-null  object
```

```
 6   expiration            12684 non-null  object
 7   gender                12684 non-null  object
 8   age                   12684 non-null  object
 9   maritalStatus         12684 non-null  object
 10  has_children          12684 non-null  int64
 11  education             12684 non-null  object
 12  income                12684 non-null  object
 13  Bar                   12577 non-null  object
 14  CoffeeHouse           12467 non-null  object
 15  CarryAway             12533 non-null  object
 16  RestaurantLessThan20  12554 non-null  object
 17  Restaurant20To50      12495 non-null  object
 18  toCoupon_GEQ15min     12684 non-null  int64
 19  toCoupon_GEQ25min     12684 non-null  int64
 20  direction_same        12684 non-null  int64
 21  direction_opp         12684 non-null  int64
 22  Y                     12684 non-null  int64
dtypes: int64(7), object(16)
memory usage: 2.2+ MB
```

```
# frequent value / mode imputation for missing values in data. This code snippet has been taken from Niralidedaniya (2022).
in_vehicle_coupon_data['Bar']=in_vehicle_coupon_data['Bar'].fillna(in_vehicle_coupon_data['Bar'].value_counts().index[0])
in_vehicle_coupon_data['CoffeeHouse']=in_vehicle_coupon_data['CoffeeHouse'].fillna(in_vehicle_coupon_data['CoffeeHouse'].value_counts().index[0])
in_vehicle_coupon_data['CarryAway']=in_vehicle_coupon_data['CarryAway'].fillna(in_vehicle_coupon_data['CarryAway'].value_counts().index[0])
in_vehicle_coupon_data['RestaurantLessThan20']=in_vehicle_coupon_data['RestaurantLessThan20'].fillna(in_vehicle_coupon_data['RestaurantLessThan20'].value_c
in_vehicle_coupon_data['Restaurant20To50']=in_vehicle_coupon_data['Restaurant20To50'].fillna(in_vehicle_coupon_data['Restaurant20To50'].value_counts().inde
#Lets check for missing values again
print('Is there any missing value present?',in_vehicle_coupon_data.isnull().values.any())
```

```
Is there any missing value present? False
```

```
from sklearn.preprocessing import OrdinalEncoder
encoder = OrdinalEncoder()
encoded_in_vehicle_coupon_data = encoder.fit_transform(in_vehicle_coupon_data)
encoded_in_vehicle_coupon_data = pd.DataFrame(encoded_in_vehicle_coupon_data, columns=in_vehicle_coupon_data.columns)
encoded_in_vehicle_coupon_data.cov() #covariance
```

	destination	passanger	weather	temperature	time	coupon	expiration	gender	age	maritalStatus	...	Bar
destination	0.504658	-0.078836	-0.035245	-0.015041	0.420743	-0.010986	-0.011497	0.002407	-0.003339	0.001797	...	-0.005564
passanger	-0.078836	0.887317	0.035703	0.040508	-0.543328	0.023840	0.034968	-0.009838	0.010415	-0.016771	...	0.022005
weather	-0.035245	0.035703	0.401445	0.210926	-0.021266	0.125609	0.005569	-0.008552	-0.027806	-0.008874	...	0.010249
temperature	-0.015041	0.040508	0.210926	0.587031	-0.065117	0.133050	0.047207	-0.009767	-0.046974	0.002288	...	0.010868
time	0.420743	-0.543328	-0.021266	-0.065117	2.072183	0.092426	-0.060532	-0.002523	-0.025719	0.005786	...	-0.009895
coupon	-0.010986	0.023840	0.125609	0.133050	0.092426	1.818577	0.099355	0.004809	0.006944	-0.000149	...	-0.015862
expiration	-0.011497	0.034968	0.005569	0.047207	-0.060532	0.099355	0.246532	-0.000314	0.007207	-0.005098	...	-0.006669
gender	0.002407	-0.009838	-0.008552	-0.009767	-0.002523	0.004809	-0.000314	0.249842	-0.067526	0.023960	...	-0.120201
age	-0.003339	0.010415	-0.027806	-0.046974	-0.025719	0.006944	0.007207	-0.067526	4.950184	-0.328927	...	0.712399
maritalStatus	0.001797	-0.016771	-0.008874	0.002288	0.005786	-0.000149	-0.005098	0.023960	-0.328927	0.693751	...	-0.118302
has_children	-0.002347	0.016028	0.003950	-0.007441	-0.005145	-0.006923	0.003918	-0.039384	0.335703	-0.177913	...	0.127863
education	0.011758	0.001656	0.015185	0.022296	-0.008154	-0.001837	-0.008597	0.014140	0.363653	0.107978	...	0.116209
income	-0.025464	-0.005402	-0.051117	-0.047347	-0.022016	0.002894	-0.013671	0.032841	0.267308	0.150888	...	0.053494
Bar	-0.005564	0.022005	0.010249	0.010868	-0.009895	-0.015862	-0.006669	-0.120201	0.712399	-0.118302	...	2.407485
CoffeeHouse	-0.007850	-0.012488	-0.005865	0.008828	-0.011495	-0.004406	-0.009675	0.045669	-0.002177	0.014938	...	0.378947
CarryAway	-0.005959	-0.017730	-0.026723	-0.027345	0.001266	-0.004440	-0.002079	-0.009576	0.216170	-0.022649	...	0.134812
RestaurantLessThan20	0.002886	-0.033238	-0.003905	-0.001147	-0.004725	0.016685	-0.006039	0.025848	-0.074016	-0.001212	...	0.139119
Restaurant20To50	-0.000269	-0.042455	0.005444	0.002082	0.019281	0.011179	-0.000336	-0.000155	-0.004063	0.055322	...	0.375264
toCoupon_GEQ15min	0.049593	0.030170	-0.038262	-0.059057	0.005156	-0.088045	0.010531	-0.001743	0.029335	-0.020447	...	0.015285
toCoupon_GEQ25min	0.045391	-0.060297	-0.041579	-0.053675	0.136276	-0.049269	-0.005304	0.000444	-0.000045	0.001348	...	0.002514
direction_same	-0.024310	-0.103995	0.004609	0.030548	0.184128	-0.040432	0.006848	-0.000923	-0.007565	0.005645	...	-0.000763
direction_opp	0.024310	0.103995	-0.004609	-0.030548	-0.184128	0.040432	-0.006848	0.000923	0.007565	-0.005645	...	0.000763
Y	-0.000671	0.024082	0.031006	0.023241	-0.033780	0.064804	-0.031952	0.010886	-0.038836	0.010348	...	-0.058434

23 rows × 23 columns

Arts Design Entertainment Sports & Media

```
# Since direction_same has same covariance values as direction_opp. It makes sense to just have one on them and reduce the noise.
in_vehicle_coupon_data = in_vehicle_coupon_data.drop(['direction_opp'], axis=1)
in_vehicle_coupon_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12684 entries, 0 to 12683
Data columns (total 22 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   destination           12684 non-null  object
 1   passanger             12684 non-null  object
 2   weather               12684 non-null  object
 3   temperature           12684 non-null  int64
 4   time                  12684 non-null  object
 5   coupon                12684 non-null  object
 6   expiration            12684 non-null  object
 7   gender                12684 non-null  object
 8   age                   12684 non-null  object
 9   maritalStatus         12684 non-null  object
 10  has_children          12684 non-null  int64
 11  education             12684 non-null  object
 12  income                12684 non-null  object
 13  Bar                   12684 non-null  object
 14  CoffeeHouse           12684 non-null  object
 15  CarryAway             12684 non-null  object
 16  RestaurantLessThan20  12684 non-null  object
 17  Restaurant20To50      12684 non-null  object
 18  toCoupon_GEQ15min     12684 non-null  int64
 19  toCoupon_GEQ25min     12684 non-null  int64
 20  direction_same        12684 non-null  int64
 21  Y                     12684 non-null  int64
dtypes: int64(6), object(16)
memory usage: 2.1+ MB
```

0 250 500 750 1000 1250 1500 1750 2000

```
#Get the correlation matrix using ordinal encoding for the categorical values
encoder = OrdinalEncoder()
encoded_in_vehicle_coupon_data = encoder.fit_transform(in_vehicle_coupon_data)
encoded_in_vehicle_coupon_data = pd.DataFrame(encoded_in_vehicle_coupon_data, columns=in_vehicle_coupon_data.columns)
correlation_matrix = encoded_in_vehicle_coupon_data.corr()
print(correlation_matrix)
```

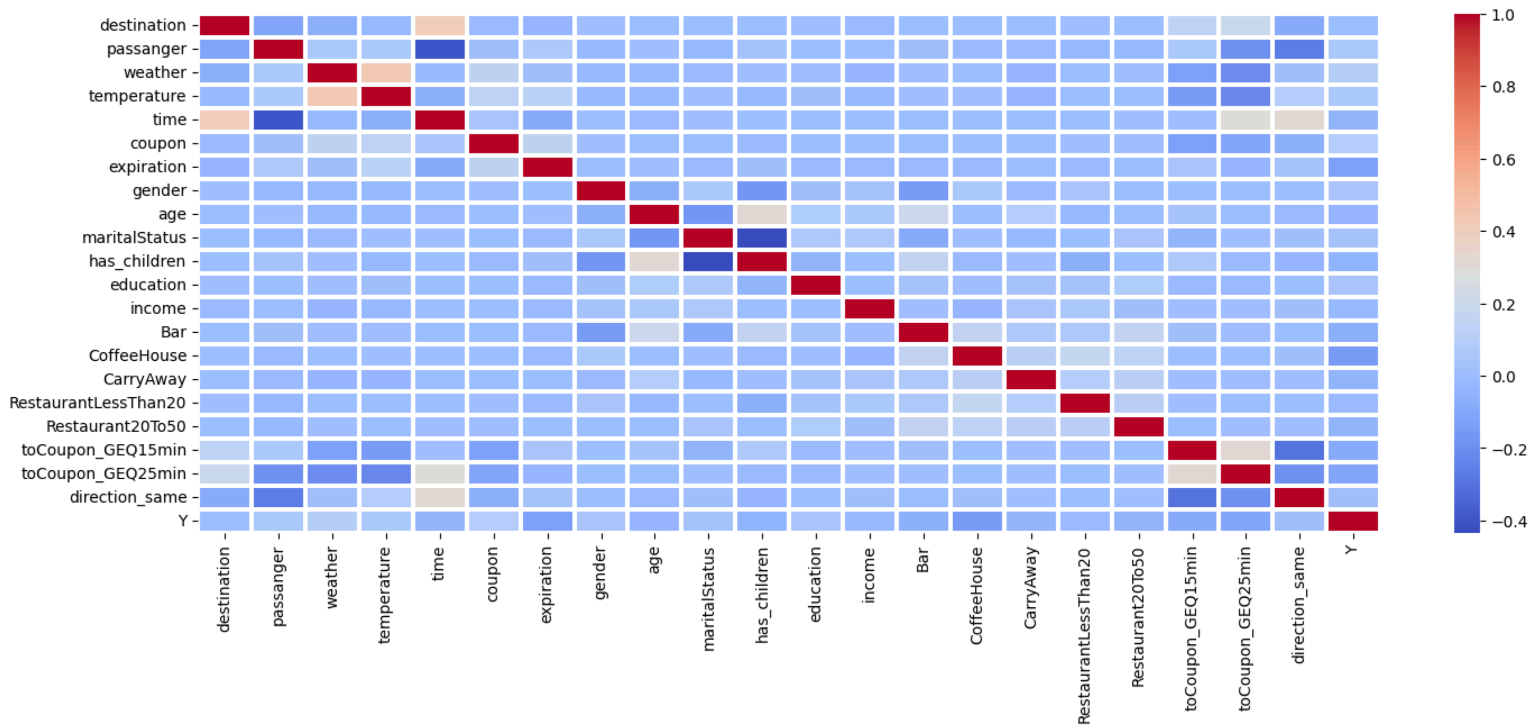
```
                      destination  passanger   weather  temperature      time  \
destination              1.000000  -0.117811 -0.078305    -0.027633  0.411437
passanger               -0.117811   1.000000  0.059821     0.056127 -0.400690
weather                 -0.078305   0.059821  1.000000     0.434497 -0.023316
temperature             -0.027633   0.056127  0.434497     1.000000 -0.059041
time                     0.411437  -0.400690 -0.023316    -0.059041  1.000000
coupon                  -0.011468   0.018767  0.147008     0.128771  0.047612
expiration              -0.032594   0.074764  0.017702     0.124090 -0.084691
gender                   0.006779  -0.020896 -0.027003    -0.025504 -0.003507
age                     -0.002112   0.004969 -0.019725    -0.027556 -0.008030
maritalStatus            0.003036  -0.021376 -0.016816     0.003585  0.004826
has_children            -0.006707   0.034542  0.012657    -0.019716 -0.007256
education                0.008793   0.000934  0.012733     0.015460 -0.003009
income                  -0.014554  -0.002329 -0.032758    -0.025091 -0.006210
Bar                     -0.005048   0.015055  0.010426     0.009142 -0.004430
CoffeeHouse             -0.007185  -0.008619 -0.006018     0.007491 -0.005192
CarryAway               -0.007676  -0.017223 -0.038593    -0.032657  0.000804
RestaurantLessThan20     0.003497  -0.030378 -0.005306    -0.001289 -0.002826
Restaurant20To50        -0.000255  -0.030401  0.005795     0.001833  0.009035
toCoupon_GEQ15min        0.140684   0.064544 -0.121698    -0.155332  0.007218
toCoupon_GEQ25min        0.197240  -0.197595 -0.202572    -0.216254  0.292231
direction_same          -0.083328  -0.268830  0.017712     0.097085  0.311467
Y                       -0.001906   0.051614  0.098800     0.061240 -0.047377

                        coupon  expiration    gender       age  maritalStatus  \
destination          -0.011468   -0.032594  0.006779 -0.002112       0.003036
passanger             0.018767    0.074764 -0.020896  0.004969      -0.021376
weather               0.147008    0.017702 -0.027003 -0.019725      -0.016816
temperature           0.128771    0.124090 -0.025504 -0.027556       0.003585
time                  0.047612   -0.084691 -0.003507 -0.008030       0.004826
coupon                1.000000    0.148383  0.007134  0.002314      -0.000132
expiration            0.148383    1.000000 -0.001264  0.006523      -0.012328
gender                0.007134   -0.001264  1.000000 -0.060720       0.057552
age                   0.002314    0.006523 -0.060720  1.000000      -0.177495
maritalStatus        -0.000132   -0.012328  0.057552 -0.177495       1.000000
has_children         -0.010422    0.016020 -0.159956  0.306306      -0.433628
education            -0.000724   -0.009198  0.015029  0.086833       0.068872
income                0.000871   -0.011180  0.026677  0.048782       0.073555
Bar                  -0.007581   -0.008656 -0.154986  0.206363      -0.091539
CoffeeHouse          -0.002124   -0.012669  0.059404 -0.000636       0.011661
CarryAway            -0.003012   -0.003832 -0.017530  0.088903      -0.024881
RestaurantLessThan20  0.010651   -0.010471  0.044519 -0.028640      -0.001253
Restaurant20To50      0.005592   -0.000457 -0.000209 -0.001232       0.044802
toCoupon_GEQ15min    -0.131571    0.042740 -0.007028  0.026571      -0.049471
```

```
toCoupon_GEQ25min    -0.112780   -0.032977  0.002743 -0.000063       0.004997
direction_same       -0.073007    0.033584 -0.004496 -0.008279       0.016504
Y                     0.097019   -0.129920  0.043969 -0.035241       0.025083

                      ...    income       Bar  CoffeeHouse  CarryAway  \
destination           ... -0.014554 -0.005048    -0.007185  -0.007676
passanger             ... -0.002329  0.015055    -0.008619  -0.017223
weather               ... -0.032758  0.010426    -0.006018  -0.038593
temperature           ... -0.025091  0.009142     0.007491  -0.032657
time                  ... -0.006210 -0.004430    -0.005192   0.000804
coupon                ...  0.000871 -0.007581    -0.002124  -0.003012
expiration            ... -0.011180 -0.008656    -0.012669  -0.003832
gender                ...  0.026677 -0.154986     0.059404  -0.017530
age                   ...  0.048782  0.206363    -0.000636   0.088903
```

```
#Heat map to visually quickly see high correlation
plt.figure(figsize=(17, 6))
sns.heatmap(correlation_matrix, cmap='coolwarm', linewidths=1.5)
plt.show()
```



There seems to be a correlation between time and destination, between temperature and weather, between marital status and has children, between passenger and time, between to coupon GEQ 15 min and same direction.

```
#Stepwise Regression for Dimensionality reduction
import statsmodels.api as sm
x_stepwise = encoded_in_vehicle_coupon_data.drop("Y", axis=1)
y_stepwise = encoded_in_vehicle_coupon_data["Y"]
# Perform stepwise regression
result_stepwise_1 = sm.OLS(y_stepwise, x_stepwise).fit()
print(result_stepwise_1.summary())
```

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:                      Y   R-squared (uncentered):                   0.587
Model:                            OLS   Adj. R-squared (uncentered):              0.586
Method:                 Least Squares   F-statistic:                              856.7
Date:                Mon, 11 Nov 2024   Prob (F-statistic):                        0.00
Time:                        05:49:27   Log-Likelihood:                         -8808.8
No. Observations:               12684   AIC:                                  1.766e+04
Df Residuals:                   12663   BIC:                                  1.782e+04
Df Model:                          21
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
```

```
destination             0.0569      0.007      8.321      0.000       0.044       0.070
passanger               0.0471      0.005      9.367      0.000       0.037       0.057
weather                 0.1170      0.007     16.382      0.000       0.103       0.131
temperature             0.0266      0.006      4.160      0.000       0.014       0.039
time                   -0.0096      0.004     -2.434      0.015      -0.017      -0.002
coupon                  0.0541      0.003     16.362      0.000       0.048       0.061
expiration             -0.1407      0.009    -15.771      0.000      -0.158      -0.123
gender                  0.0866      0.009     10.012      0.000       0.070       0.104
age                     0.0025      0.002      1.189      0.234      -0.002       0.007
maritalStatus           0.0635      0.005     12.183      0.000       0.053       0.074
has_children            0.0444      0.010      4.483      0.000       0.025       0.064
education               0.0200      0.002      8.762      0.000       0.016       0.025
income                  0.0014      0.002      0.820      0.412      -0.002       0.005
Bar                     0.0008      0.003      0.281      0.779      -0.005       0.007
CoffeeHouse            -0.0363      0.003    -12.574      0.000      -0.042      -0.031
CarryAway               0.0014      0.004      0.354      0.723      -0.006       0.009
RestaurantLessThan20    0.0150      0.004      3.935      0.000       0.008       0.022
Restaurant20To50       -0.0019      0.003     -0.638      0.524      -0.008       0.004
toCoupon_GEQ15min       0.0237      0.009      2.502      0.012       0.005       0.042
toCoupon_GEQ25min      -0.0321      0.016     -2.039      0.041      -0.063      -0.001
direction_same          0.1026      0.013      8.132      0.000       0.078       0.127
==============================================================================
Omnibus:                77704.989   Durbin-Watson:                   1.682
Prob(Omnibus):              0.000   Jarque-Bera (JB):             1296.009
Skew:                      -0.228   Prob(JB):                    3.76e-282
Kurtosis:                   1.502   Cond. No.                         31.5
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

I choose alpha to be 0.05. Coefficients having a p-value of 0.05 or less will be statistically significant. Bar has 0.779 for p-value. Bar will be dropped. It is the least statistically significant.

```
x_stepwise_2 = x_stepwise.drop("Bar", axis=1)
result_stepwise_2 = sm.OLS(y_stepwise, x_stepwise_2).fit()
print(result_stepwise_2.summary())
```

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:                      Y   R-squared (uncentered):                   0.587
Model:                            OLS   Adj. R-squared (uncentered):              0.586
Method:                 Least Squares   F-statistic:                              899.5
Date:                Mon, 11 Nov 2024   Prob (F-statistic):                        0.00
Time:                        05:49:27   Log-Likelihood:                         -8808.9
No. Observations:               12684   AIC:                                  1.766e+04
Df Residuals:                   12664   BIC:                                  1.781e+04
Df Model:                          20
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
destination             0.0570      0.007      8.332      0.000       0.044       0.070
passanger               0.0472      0.005      9.400      0.000       0.037       0.057
weather                 0.1172      0.007     16.463      0.000       0.103       0.131
temperature             0.0266      0.006      4.172      0.000       0.014       0.039
time                   -0.0095      0.004     -2.426      0.015      -0.017      -0.002
coupon                  0.0541      0.003     16.380      0.000       0.048       0.061
expiration             -0.1407      0.009    -15.770      0.000      -0.158      -0.123
gender                  0.0863      0.009     10.041      0.000       0.069       0.103
age                     0.0026      0.002      1.265      0.206      -0.001       0.007
maritalStatus           0.0636      0.005     12.229      0.000       0.053       0.074
has_children            0.0448      0.010      4.567      0.000       0.026       0.064
education               0.0201      0.002      8.790      0.000       0.016       0.025
income                  0.0014      0.002      0.833      0.405      -0.002       0.005
CoffeeHouse            -0.0362      0.003    -12.713      0.000      -0.042      -0.031
CarryAway               0.0015      0.004      0.368      0.713      -0.006       0.009
RestaurantLessThan20    0.0150      0.004      3.966      0.000       0.008       0.022
Restaurant20To50       -0.0018      0.003     -0.599      0.549      -0.008       0.004
toCoupon_GEQ15min       0.0238      0.009      2.519      0.012       0.005       0.042
toCoupon_GEQ25min      -0.0319      0.016     -2.032      0.042      -0.063      -0.001
direction_same          0.1027      0.013      8.147      0.000       0.078       0.127
==============================================================================
Omnibus:                77832.632   Durbin-Watson:                   1.682
Prob(Omnibus):              0.000   Jarque-Bera (JB):             1295.135
Skew:                      -0.228   Prob(JB):                    5.82e-282
Kurtosis:                   1.503   Cond. No.                         29.7
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In the second iteration, CarryAway is least statistically significant because it has highest p-value of 0.713 which is greater than alpha of 0.05. CarryAway should be dropped.

```
x_stepwise_3 = x_stepwise_2.drop("CarryAway", axis=1)
result_stepwise_3 = sm.OLS(y_stepwise, x_stepwise_3).fit()
print(result_stepwise_3.summary())
```

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:                      Y   R-squared (uncentered):                   0.587
Model:                            OLS   Adj. R-squared (uncentered):              0.586
Method:                 Least Squares   F-statistic:                              946.9
Date:                Mon, 11 Nov 2024   Prob (F-statistic):                        0.00
Time:                        05:49:27   Log-Likelihood:                         -8808.9
No. Observations:               12684   AIC:                                  1.766e+04
Df Residuals:                   12665   BIC:                                  1.780e+04
Df Model:                          19
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
destination              0.0570      0.007      8.337      0.000       0.044       0.070
passanger                0.0472      0.005      9.409      0.000       0.037       0.057
weather                  0.1173      0.007     16.477      0.000       0.103       0.131
temperature              0.0266      0.006      4.171      0.000       0.014       0.039
time                    -0.0095      0.004     -2.420      0.016      -0.017      -0.002
coupon                   0.0541      0.003     16.396      0.000       0.048       0.061
expiration              -0.1406      0.009    -15.767      0.000      -0.158      -0.123
gender                   0.0863      0.009     10.040      0.000       0.069       0.103
age                      0.0027      0.002      1.312      0.189      -0.001       0.007
maritalStatus            0.0637      0.005     12.246      0.000       0.053       0.074
has_children             0.0448      0.010      4.570      0.000       0.026       0.064
education                0.0201      0.002      8.805      0.000       0.016       0.025
income                   0.0015      0.002      0.859      0.390      -0.002       0.005
CoffeeHouse             -0.0361      0.003    -12.757      0.000      -0.042      -0.031
RestaurantLessThan20     0.0151      0.004      4.005      0.000       0.008       0.023
Restaurant20To50        -0.0016      0.003     -0.559      0.576      -0.007       0.004
toCoupon_GEQ15min        0.0240      0.009      2.532      0.011       0.005       0.042
toCoupon_GEQ25min       -0.0319      0.016     -2.030      0.042      -0.063      -0.001
direction_same           0.1029      0.013      8.158      0.000       0.078       0.128
==============================================================================
Omnibus:                    77965.192   Durbin-Watson:                   1.682
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1294.195
Skew:                          -0.228   Prob(JB):                    9.31e-282
Kurtosis:                       1.503   Cond. No.                         29.4
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In the third iteration, Restaurant20To50 is least statistically significant because it has highest p-value of 0.576 which is greater than alpha of 0.05. Restaurant20To50 should be dropped.

```
x_stepwise_4 = x_stepwise_3.drop("Restaurant20To50", axis=1)
result_stepwise_4 = sm.OLS(y_stepwise, x_stepwise_4).fit()
print(result_stepwise_4.summary())
```

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:                      Y   R-squared (uncentered):                   0.587
Model:                            OLS   Adj. R-squared (uncentered):              0.586
Method:                 Least Squares   F-statistic:                              999.6
Date:                Mon, 11 Nov 2024   Prob (F-statistic):                        0.00
Time:                        05:49:28   Log-Likelihood:                         -8809.1
No. Observations:               12684   AIC:                                  1.765e+04
Df Residuals:                   12666   BIC:                                  1.779e+04
Df Model:                          18
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
destination              0.0569      0.007      8.326      0.000       0.044       0.070
passanger                0.0472      0.005      9.402      0.000       0.037       0.057
weather                  0.1169      0.007     16.487      0.000       0.103       0.131
temperature              0.0265      0.006      4.161      0.000       0.014       0.039
time                    -0.0096      0.004     -2.436      0.015      -0.017      -0.002
coupon                   0.0541      0.003     16.388      0.000       0.048       0.061
expiration              -0.1407      0.009    -15.782      0.000      -0.158      -0.123
gender                   0.0862      0.009     10.031      0.000       0.069       0.103
age                      0.0026      0.002      1.300      0.193      -0.001       0.007
maritalStatus            0.0633      0.005     12.288      0.000       0.053       0.073
```

```
has_children            0.0444      0.010      4.539      0.000       0.025       0.064
education               0.0200      0.002      8.798      0.000       0.016       0.024
income                  0.0014      0.002      0.832      0.405      -0.002       0.005
CoffeeHouse            -0.0363      0.003    -13.018      0.000      -0.042      -0.031
RestaurantLessThan20    0.0149      0.004      3.967      0.000       0.008       0.022
toCoupon_GEQ15min       0.0237      0.009      2.510      0.012       0.005       0.042
toCoupon_GEQ25min      -0.0321      0.016     -2.042      0.041      -0.063      -0.001
direction_same          0.1027      0.013      8.146      0.000       0.078       0.127
==============================================================================
Omnibus:                    77733.204   Durbin-Watson:                   1.682
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1296.124
Skew:                          -0.229   Prob(JB):                    3.55e-282
Kurtosis:                       1.502   Cond. No.                         28.1
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In the fourth iteration, income is least statistically significant because it has highest p-value of 0.405 which is greater than alpha of 0.05. income should be dropped.

```
x_stepwise_5 = x_stepwise_4.drop("income", axis=1)
result_stepwise_5 = sm.OLS(y_stepwise, x_stepwise_5).fit()
print(result_stepwise_5.summary())
```

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:                      Y   R-squared (uncentered):                   0.587
Model:                            OLS   Adj. R-squared (uncentered):              0.586
Method:                 Least Squares   F-statistic:                              1058.
Date:                Mon, 11 Nov 2024   Prob (F-statistic):                        0.00
Time:                        05:49:28   Log-Likelihood:                         -8809.4
No. Observations:               12684   AIC:                                  1.765e+04
Df Residuals:                   12667   BIC:                                  1.778e+04
Df Model:                          17
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
destination             0.0570      0.007      8.345      0.000       0.044       0.070
passanger               0.0474      0.005      9.456      0.000       0.038       0.057
weather                 0.1173      0.007     16.564      0.000       0.103       0.131
temperature             0.0266      0.006      4.172      0.000       0.014       0.039
time                   -0.0095      0.004     -2.419      0.016      -0.017      -0.002
coupon                  0.0542      0.003     16.455      0.000       0.048       0.061
expiration             -0.1407      0.009    -15.779      0.000      -0.158      -0.123
gender                  0.0867      0.009     10.112      0.000       0.070       0.103
age                     0.0028      0.002      1.384      0.166      -0.001       0.007
maritalStatus           0.0641      0.005     12.716      0.000       0.054       0.074
has_children            0.0451      0.010      4.632      0.000       0.026       0.064
education               0.0200      0.002      8.825      0.000       0.016       0.024
CoffeeHouse            -0.0364      0.003    -13.027      0.000      -0.042      -0.031
RestaurantLessThan20    0.0152      0.004      4.061      0.000       0.008       0.023
toCoupon_GEQ15min       0.0242      0.009      2.565      0.010       0.006       0.043
toCoupon_GEQ25min      -0.0318      0.016     -2.023      0.043      -0.063      -0.001
direction_same          0.1033      0.013      8.208      0.000       0.079       0.128
==============================================================================
Omnibus:                    78102.225   Durbin-Watson:                   1.682
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1293.019
Skew:                          -0.228   Prob(JB):                    1.68e-281
Kurtosis:                       1.504   Cond. No.                         24.7
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In the fifth iteration, age is least statistically significant because it has highest p-value of 0.166 which is greater than alpha of 0.05. age should be dropped.

```
x_stepwise_6 = x_stepwise_5.drop("age", axis=1)
result_stepwise_6 = sm.OLS(y_stepwise, x_stepwise_6).fit()
print(result_stepwise_6.summary())
```

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:                      Y   R-squared (uncentered):                   0.587
Model:                            OLS   Adj. R-squared (uncentered):              0.586
Method:                 Least Squares   F-statistic:                              1124.
Date:                Mon, 11 Nov 2024   Prob (F-statistic):                        0.00
Time:                        05:49:28   Log-Likelihood:                         -8810.4
```

```
No. Observations:               12684   AIC:                             1.765e+04
Df Residuals:                   12668   BIC:                             1.777e+04
Df Model:                          16
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
destination              0.0573      0.007      8.395      0.000       0.044       0.071
passanger                0.0476      0.005      9.511      0.000       0.038       0.057
weather                  0.1179      0.007     16.677      0.000       0.104       0.132
temperature              0.0266      0.006      4.178      0.000       0.014       0.039
time                    -0.0094      0.004     -2.393      0.017      -0.017      -0.002
coupon                   0.0545      0.003     16.551      0.000       0.048       0.061
expiration              -0.1405      0.009    -15.755      0.000      -0.158      -0.123
gender                   0.0869      0.009     10.147      0.000       0.070       0.104
maritalStatus            0.0644      0.005     12.772      0.000       0.054       0.074
has_children             0.0496      0.009      5.403      0.000       0.032       0.068
education                0.0205      0.002      9.148      0.000       0.016       0.025
CoffeeHouse             -0.0362      0.003    -12.978      0.000      -0.042      -0.031
RestaurantLessThan20     0.0153      0.004      4.082      0.000       0.008       0.023
toCoupon_GEQ15min        0.0248      0.009      2.636      0.008       0.006       0.043
toCoupon_GEQ25min       -0.0313      0.016     -1.995      0.046      -0.062      -0.001
direction_same           0.1040      0.013      8.269      0.000       0.079       0.129
==============================================================================
Omnibus:                78704.924   Durbin-Watson:                   1.682
Prob(Omnibus):              0.000   Jarque-Bera (JB):             1288.500
Skew:                      -0.228   Prob(JB):                    1.61e-280
Kurtosis:                   1.507   Cond. No.                         22.4
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Therefore, age, income, Restaurant20To50, CarryAway and Bar need to be dropped from encoded_in_vehicle_coupon_data to create a dataset that is dimensionally reduced due to stepwise regression.

```
stepwise_reduced_data = encoded_in_vehicle_coupon_data.drop(["Bar", "Restaurant20To50", "CarryAway", "income", "age"], axis=1)
stepwise_reduced_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12684 entries, 0 to 12683
Data columns (total 17 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   destination           12684 non-null  float64
 1   passanger             12684 non-null  float64
 2   weather               12684 non-null  float64
 3   temperature           12684 non-null  float64
 4   time                  12684 non-null  float64
 5   coupon                12684 non-null  float64
 6   expiration            12684 non-null  float64
 7   gender                12684 non-null  float64
 8   maritalStatus         12684 non-null  float64
 9   has_children          12684 non-null  float64
 10  education             12684 non-null  float64
 11  CoffeeHouse           12684 non-null  float64
 12  RestaurantLessThan20  12684 non-null  float64
 13  toCoupon_GEQ15min     12684 non-null  float64
 14  toCoupon_GEQ25min     12684 non-null  float64
 15  direction_same        12684 non-null  float64
 16  Y                     12684 non-null  float64
dtypes: float64(17)
memory usage: 1.6 MB
```

```
#Now I will do forward feature selection for dimensionality reduction of encoded_in_vehicle_coupon_data
from sklearn.feature_selection import SequentialFeatureSelector as sfs
from sklearn.linear_model import LinearRegression


lreg = LinearRegression()
X_forward_feature_selection = encoded_in_vehicle_coupon_data.drop(['Y'], axis=1)
y_forward_feature_selection = encoded_in_vehicle_coupon_data['Y']
#I wasn to keep the same number of features as stepwise regression, so I picked 16
sfs1 = sfs(estimator=lreg, n_features_to_select=16, direction='forward', scoring='neg_mean_squared_error')
sfs1 = sfs1.fit(X_forward_feature_selection, y_forward_feature_selection)
selected_features_indices = sfs1.get_support(indices=True)
feature_names = X_forward_feature_selection.columns
# Get the names of the selected features
selected_features_forward = feature_names[selected_features_indices]
print("Selected feature names:", selected_features_forward)
```

```
Selected feature names: Index(['destination', 'passanger', 'weather', 'time', 'coupon', 'expiration',
       'gender', 'age', 'has_children', 'education', 'income', 'CoffeeHouse',
       'CarryAway', 'Restaurant20To50', 'toCoupon_GEQ15min',
       'toCoupon_GEQ25min'],
      dtype='object')
```

```
#Below code snippet from https://stackoverflow.com/questions/72985935/how-to-run-machine-learning-algorithms-in-gpu
unselected_features_forward = list(set(feature_names) - set(selected_features_forward))
print("Unselected feature names by forward feature selection ", unselected_features_forward)
```

```
Unselected feature names by forward feature selection  ['maritalStatus', 'direction_same', 'temperature', 'Bar', 'RestaurantLessThan20']
```

```
forward_feature_reduced_data = encoded_in_vehicle_coupon_data.drop(["Bar", "RestaurantLessThan20", "direction_same", "temperature", "maritalStatus"], axis=
forward_feature_reduced_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12684 entries, 0 to 12683
Data columns (total 17 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   destination        12684 non-null  float64
 1   passanger          12684 non-null  float64
 2   weather            12684 non-null  float64
 3   time               12684 non-null  float64
 4   coupon             12684 non-null  float64
 5   expiration         12684 non-null  float64
 6   gender             12684 non-null  float64
 7   age                12684 non-null  float64
 8   has_children       12684 non-null  float64
 9   education          12684 non-null  float64
 10  income             12684 non-null  float64
 11  CoffeeHouse        12684 non-null  float64
 12  CarryAway          12684 non-null  float64
 13  Restaurant20To50   12684 non-null  float64
 14  toCoupon_GEQ15min  12684 non-null  float64
 15  toCoupon_GEQ25min  12684 non-null  float64
 16  Y                  12684 non-null  float64
dtypes: float64(17)
memory usage: 1.6 MB
```

Stepwise Regression and Forward Feature selection for dimensionality reduction gave different results resulting in different columns being dropped. Let's now see the results of Backward Feature elimination.

```
X_backward_feature_elimination = encoded_in_vehicle_coupon_data.drop(['Y'], axis=1)
y_backward_feature_elimination = encoded_in_vehicle_coupon_data['Y']
#I wasn to keep the same number of features as stepwise regression and forward feature selection for comparison, so I picked 16
sfs2 = sfs(estimator=lreg, n_features_to_select=16, direction = 'backward', scoring='neg_mean_squared_error')
sfs2 = sfs2.fit(X_backward_feature_elimination, y_backward_feature_elimination)
selected_features_indices_2 = sfs2.get_support(indices=True)
feature_names_2 = X_backward_feature_elimination.columns
# Get the names of the selected features
selected_features_backward = feature_names_2[selected_features_indices_2]
print("Selected feature names for backward feature elimination:", selected_features_backward)
```

```
Selected feature names for backward feature elimination: Index(['destination', 'passanger', 'weather', 'time', 'coupon', 'expiration',
       'gender', 'age', 'has_children', 'education', 'income', 'CoffeeHouse',
       'CarryAway', 'Restaurant20To50', 'toCoupon_GEQ15min',
       'toCoupon_GEQ25min'],
      dtype='object')
```

```
#Below code snippet from https://stackoverflow.com/questions/72985935/how-to-run-machine-learning-algorithms-in-gpu
unselected_features_backward = list(set(feature_names_2) - set(selected_features_backward))
print("Unselected feature names for backward feature elimination ", unselected_features_forward)
```

```
Unselected feature names for backward feature elimination  ['maritalStatus', 'direction_same', 'temperature', 'Bar', 'RestaurantLessThan20']
```

```
backward_feature_reduced_data = encoded_in_vehicle_coupon_data.drop(["Bar", "RestaurantLessThan20", "direction_same", "temperature", "maritalStatus"], axis
backward_feature_reduced_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12684 entries, 0 to 12683
Data columns (total 17 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   destination        12684 non-null  float64
 1   passanger          12684 non-null  float64
 2   weather            12684 non-null  float64
 3   time               12684 non-null  float64
 4   coupon             12684 non-null  float64
```

```
 5   expiration         12684 non-null  float64
 6   gender             12684 non-null  float64
 7   age                12684 non-null  float64
 8   has_children       12684 non-null  float64
 9   education          12684 non-null  float64
 10  income             12684 non-null  float64
 11  CoffeeHouse        12684 non-null  float64
 12  CarryAway          12684 non-null  float64
 13  Restaurant20To50   12684 non-null  float64
 14  toCoupon_GEQ15min  12684 non-null  float64
 15  toCoupon_GEQ25min  12684 non-null  float64
 16  Y                  12684 non-null  float64
dtypes: float64(17)
memory usage: 1.6 MB
```

It is thus observed that the results of Forward feature selection and Backward feature elimination are the same and give the same reduced dataset.

I will now run the classification algorithms on the 2 dimensionally reduced datasets for comparison. The 2 data sets are: the one reduced using stepwise regression and the other reduced using backward feature elimination/forward feature selection.

Random forest on dataset reduced using stepwise regression

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.metrics import roc_auc_score, roc_curve
X_random_forest_stepwise_data = stepwise_reduced_data.drop('Y', axis=1)
y_random_forest_stepwise_data = stepwise_reduced_data['Y']
X_random_forest_stepwise_train, X_random_forest_stepwise_test, y_random_forest_stepwise_train, y_random_forest_stepwise_test = train_test_split(X_random_fo
rf_stepwise = RandomForestClassifier(n_estimators=100, random_state=50)
rf_stepwise.fit(X_random_forest_stepwise_train, y_random_forest_stepwise_train)
y_pred_stepwise = rf_stepwise.predict(X_random_forest_stepwise_test)
print("Accuracy:", accuracy_score(y_random_forest_stepwise_test, y_pred_stepwise))
print("Classification Report:\n", classification_report(y_random_forest_stepwise_test, y_pred_stepwise))
y_pred_prob_random_forest_stepwise = rf_stepwise.predict_proba(X_random_forest_stepwise_test)[:, 1] #make predictions
auc_random_forest_stepwise = roc_auc_score(y_random_forest_stepwise_test, y_pred_prob_random_forest_stepwise)
print("AUC:", auc_random_forest_stepwise)
```

```
Accuracy: 0.6862435947970044
Classification Report:
               precision    recall  f1-score   support

         0.0       0.64      0.61      0.63      1087
         1.0       0.72      0.74      0.73      1450

    accuracy                           0.69      2537
   macro avg       0.68      0.68      0.68      2537
weighted avg       0.68      0.69      0.69      2537

AUC: 0.7351197538305365
```

Random forest on dataset reduced using forward feature selection/backward feature elimination

```
X_random_forest_backward_data = backward_feature_reduced_data.drop('Y', axis=1)
y_random_forest_backward_data = backward_feature_reduced_data['Y']
X_random_forest_backward_train, X_random_forest_backward_test, y_random_forest_backward_train, y_random_forest_backward_test = train_test_split(X_random_fo
rf_backward = RandomForestClassifier(n_estimators=100, random_state=50)
rf_backward.fit(X_random_forest_backward_train, y_random_forest_backward_train)
y_pred_backward = rf_backward.predict(X_random_forest_backward_test)
print("Accuracy:", accuracy_score(y_random_forest_backward_test, y_pred_backward))
print("Classification Report:\n", classification_report(y_random_forest_backward_test, y_pred_backward))
y_pred_prob_random_forest_backward = rf_backward.predict_proba(X_random_forest_backward_test)[:, 1] #make predictions
auc_random_forest_backward = roc_auc_score(y_random_forest_backward_test, y_pred_prob_random_forest_backward)
print("AUC:", auc_random_forest_backward)
```

```
Accuracy: 0.7335435553803705
Classification Report:
               precision    recall  f1-score   support

         0.0       0.70      0.65      0.68      1087
         1.0       0.75      0.79      0.77      1450

    accuracy                           0.73      2537
   macro avg       0.73      0.72      0.73      2537
weighted avg       0.73      0.73      0.73      2537

AUC: 0.7942876629762395
```

Logistic Regression on dataset reduced using stepwise regression

```
from sklearn.linear_model import LogisticRegression
X_logistic_reg_stepwise_data = stepwise_reduced_data.drop('Y', axis=1)
y_logistic_reg_stepwise_data = stepwise_reduced_data['Y']
X_logistic_reg_stepwise_train, X_logistic_reg_stepwise_test, y_logistic_reg_stepwise_train, y_logistic_reg_stepwise_test = train_test_split(X_logistic_reg_
logistic_stepwise_model = LogisticRegression()
logistic_stepwise_model.fit(X_logistic_reg_stepwise_train, y_logistic_reg_stepwise_train)
y_pred_logistic_reg_stepwise = logistic_stepwise_model.predict(X_logistic_reg_stepwise_test)
print("Accuracy:", accuracy_score(y_logistic_reg_stepwise_test, y_pred_logistic_reg_stepwise))
print("Classification Report:\n", classification_report(y_logistic_reg_stepwise_test, y_pred_logistic_reg_stepwise))
y_pred_prob_logistic_reg_stepwise = logistic_stepwise_model.predict_proba(X_logistic_reg_stepwise_test)[:, 1] #make predictions
auc_logistic_reg_stepwise = roc_auc_score(y_logistic_reg_stepwise_test, y_pred_prob_logistic_reg_stepwise)
print("AUC:", auc_logistic_reg_stepwise)
```

```
Accuracy: 0.6243594797004336
Classification Report:
               precision    recall  f1-score   support

         0.0       0.59      0.42      0.49      1087
         1.0       0.64      0.77      0.70      1450

    accuracy                           0.62      2537
   macro avg       0.61      0.60      0.60      2537
weighted avg       0.62      0.62      0.61      2537

AUC: 0.66001966817879
```

Logistic Regression on dataset reduced using forward feature selection/backward feature elimination

```
X_logistic_reg_backward_data = backward_feature_reduced_data.drop('Y', axis=1)
y_logistic_reg_backward_data = backward_feature_reduced_data['Y']
X_logistic_reg_backward_train, X_logistic_reg_backward_test, y_logistic_reg_backward_train, y_logistic_reg_backward_test = train_test_split(X_logistic_reg_
logistic_backward_model = LogisticRegression()
logistic_backward_model.fit(X_logistic_reg_backward_train, y_logistic_reg_backward_train)
y_pred_logistic_reg_backward = logistic_backward_model.predict(X_logistic_reg_backward_test)
print("Accuracy:", accuracy_score(y_logistic_reg_backward_test, y_pred_logistic_reg_backward))
print("Classification Report:\n", classification_report(y_logistic_reg_backward_test, y_pred_logistic_reg_backward))
y_pred_prob_logistic_reg_backward = logistic_backward_model.predict_proba(X_logistic_reg_backward_test)[:, 1] #make predictions
auc_logistic_reg_backward = roc_auc_score(y_logistic_reg_backward_test, y_pred_prob_logistic_reg_backward)
print("AUC:", auc_logistic_reg_backward)
```

```
Accuracy: 0.6267244777296019
Classification Report:
               precision    recall  f1-score   support

         0.0       0.59      0.42      0.49      1087
         1.0       0.64      0.78      0.70      1450

    accuracy                           0.63      2537
   macro avg       0.62      0.60      0.60      2537
weighted avg       0.62      0.63      0.61      2537

AUC: 0.6605948037940551
```

k Nearest Neighbours (k-NN) on dataset reduced using stepwise regression

```
from sklearn.neighbors import KNeighborsClassifier
X_knn_stepwise_data = stepwise_reduced_data.drop('Y', axis=1)
y_knn_stepwise_data = stepwise_reduced_data['Y']
X_knn_stepwise_train, X_knn_stepwise_test, y_knn_stepwise_train, y_knn_stepwise_test = train_test_split(X_knn_stepwise_data, y_knn_stepwise_data, test_size
k = 5 # Number of neighbors
knn_stepwise = KNeighborsClassifier(n_neighbors=k)
knn_stepwise.fit(X_knn_stepwise_train, y_knn_stepwise_train)
y_pred_knn_stepwise = knn_stepwise.predict(X_knn_stepwise_test)
print("Accuracy:", accuracy_score(y_knn_stepwise_test, y_pred_knn_stepwise))
print("Classification Report:\n", classification_report(y_knn_stepwise_test, y_pred_knn_stepwise))
y_pred_prob_knn_stepwise = knn_stepwise.predict_proba(X_knn_stepwise_test)[:, 1] #make predictions
auc_knn_stepwise = roc_auc_score(y_knn_stepwise_test, y_pred_prob_knn_stepwise)
print("AUC:", auc_knn_stepwise)
```

```
Accuracy: 0.6846669294442255
Classification Report:
               precision    recall  f1-score   support

         0.0       0.64      0.59      0.62      1087
         1.0       0.71      0.75      0.73      1450
```

```
    accuracy                           0.68      2537
   macro avg       0.68      0.67      0.67      2537
weighted avg       0.68      0.68      0.68      2537

AUC: 0.7027078640992291
```

k Nearest Neighbours (k-NN) on dataset reduced using forward feature selection/backward feature elimination

```
X_knn_backward_data = backward_feature_reduced_data.drop('Y', axis=1)
y_knn_backward_data = backward_feature_reduced_data['Y']
X_knn_backward_train, X_knn_backward_test, y_knn_backward_train, y_knn_backward_test = train_test_split(X_knn_backward_data, y_knn_backward_data, test_size
k = 5 # Number of neighbors
knn_backward = KNeighborsClassifier(n_neighbors=k)
knn_backward.fit(X_knn_backward_train, y_knn_backward_train)
y_pred_knn_backward = knn_backward.predict(X_knn_backward_test)
print("Accuracy:", accuracy_score(y_knn_backward_test, y_pred_knn_backward))
print("Classification Report:\n", classification_report(y_knn_backward_test, y_pred_knn_backward))
y_pred_prob_knn_backward = knn_backward.predict_proba(X_knn_backward_test)[:, 1] #make predictions
auc_knn_backward = roc_auc_score(y_knn_backward_test, y_pred_prob_knn_backward)
print("AUC:", auc_knn_backward)
```

```
Accuracy: 0.6460386283011431
Classification Report:
               precision    recall  f1-score   support

         0.0       0.60      0.54      0.57      1087
         1.0       0.68      0.73      0.70      1450

    accuracy                           0.65      2537
   macro avg       0.64      0.63      0.63      2537
weighted avg       0.64      0.65      0.64      2537

AUC: 0.6774247374932589
```

Naïve Bayes on dataset reduced using stepwise regression. I will use Gaussian Naïve Bayes.

```
from sklearn.naive_bayes import GaussianNB
X_nb_stepwise_data = stepwise_reduced_data.drop('Y', axis=1)
y_nb_stepwise_data = stepwise_reduced_data['Y']
X_nb_stepwise_train, X_nb_stepwise_test, y_nb_stepwise_train, y_nb_stepwise_test = train_test_split(X_nb_stepwise_data, y_nb_stepwise_data, test_size=0.2,
nb_stepwise_model = GaussianNB()
nb_stepwise_model.fit(X_nb_stepwise_train, y_nb_stepwise_train)
y_pred_nb_stepwise = nb_stepwise_model.predict(X_nb_stepwise_test)
print("Accuracy:", accuracy_score(y_nb_stepwise_test, y_pred_nb_stepwise))
print("Classification Report:\n", classification_report(y_nb_stepwise_test, y_pred_nb_stepwise))
y_pred_prob_nb_stepwise = nb_stepwise_model.predict_proba(X_nb_stepwise_test)[:, 1] #make predictions
auc_nb_stepwise = roc_auc_score(y_nb_stepwise_test, y_pred_prob_nb_stepwise)
print("AUC:", auc_nb_stepwise)
```

```
Accuracy: 0.5880961765865195
Classification Report:
               precision    recall  f1-score   support

         0.0       0.53      0.34      0.41      1087
         1.0       0.61      0.78      0.68      1450

    accuracy                           0.59      2537
   macro avg       0.57      0.56      0.55      2537
weighted avg       0.58      0.59      0.57      2537

AUC: 0.6340354661675602
```

Naïve Bayes on dataset reduced using forward feature selection/backward feature elimination

```
X_nb_backward_data = backward_feature_reduced_data.drop('Y', axis=1)
y_nb_backward_data = backward_feature_reduced_data['Y']
X_nb_backward_train, X_nb_backward_test, y_nb_backward_train, y_nb_backward_test = train_test_split(X_nb_backward_data, y_nb_backward_data, test_size=0.2,
nb_backward_model = GaussianNB()
nb_backward_model.fit(X_nb_backward_train, y_nb_backward_train)
y_pred_nb_backward = nb_backward_model.predict(X_nb_backward_test)
print("Accuracy:", accuracy_score(y_nb_backward_test, y_pred_nb_backward))
print("Classification Report:\n", classification_report(y_nb_backward_test, y_pred_nb_backward))
y_pred_prob_nb_backward = nb_backward_model.predict_proba(X_nb_backward_test)[:, 1] #make predictions
auc_nb_backward = roc_auc_score(y_nb_backward_test, y_pred_prob_nb_backward)
print("AUC:", auc_nb_backward)
```

```
Accuracy: 0.5904611746156878
Classification Report:
               precision    recall  f1-score   support

         0.0       0.53      0.34      0.42      1087
         1.0       0.61      0.78      0.68      1450

    accuracy                           0.59      2537
   macro avg       0.57      0.56      0.55      2537
weighted avg       0.58      0.59      0.57      2537

AUC: 0.6393308133743615
```

Decision Tree on dataset reduced using stepwise regression

```
from sklearn.tree import DecisionTreeClassifier
X_decision_tree_stepwise_data = stepwise_reduced_data.drop('Y', axis=1)
y_decision_tree_stepwise_data = stepwise_reduced_data['Y']
X_dt_stepwise_train, X_dt_stepwise_test, y_dt_stepwise_train, y_dt_stepwise_test = train_test_split(X_decision_tree_stepwise_data, y_decision_tree_stepwise
dt_stepwise_model = DecisionTreeClassifier()
dt_stepwise_model.fit(X_dt_stepwise_train, y_dt_stepwise_train)
y_pred_dt_stepwise = dt_stepwise_model.predict(X_dt_stepwise_test)
print("Accuracy:", accuracy_score(y_dt_stepwise_test, y_pred_dt_stepwise))
print("Classification Report:\n", classification_report(y_dt_stepwise_test, y_pred_dt_stepwise))
y_pred_prob_dt_stepwise = dt_stepwise_model.predict_proba(X_dt_stepwise_test)[:, 1] #make predictions
auc_dt_stepwise = roc_auc_score(y_dt_stepwise_test, y_pred_prob_dt_stepwise)
print("AUC:", auc_dt_stepwise)
```

```
Accuracy: 0.6590461174615688
Classification Report:
               precision    recall  f1-score   support

         0.0       0.60      0.63      0.61      1087
         1.0       0.71      0.68      0.70      1450

    accuracy                           0.66      2537
   macro avg       0.65      0.66      0.65      2537
weighted avg       0.66      0.66      0.66      2537

AUC: 0.659372521650858
```

Decision Tree on dataset reduced using forward feature selection/backward feature elimination

```
X_decision_tree_backward_data = backward_feature_reduced_data.drop('Y', axis=1)
y_decision_tree_backward_data = backward_feature_reduced_data['Y']
X_dt_backward_train, X_dt_backward_test, y_dt_backward_train, y_dt_backward_test = train_test_split(X_decision_tree_backward_data, y_decision_tree_backward
dt_backward_model = DecisionTreeClassifier()
dt_backward_model.fit(X_dt_backward_train, y_dt_backward_train)
y_pred_dt_backward = dt_backward_model.predict(X_dt_backward_test)
print("Accuracy:", accuracy_score(y_dt_backward_test, y_pred_dt_backward))
print("Classification Report:\n", classification_report(y_dt_backward_test, y_pred_dt_backward))
y_pred_prob_dt_backward = dt_backward_model.predict_proba(X_dt_backward_test)[:, 1] #make predictions
auc_dt_backward = roc_auc_score(y_dt_backward_test, y_pred_prob_dt_backward)
print("AUC:", auc_dt_backward)
```

```
Accuracy: 0.6637761135199054
Classification Report:
               precision    recall  f1-score   support

         0.0       0.60      0.64      0.62      1087
         1.0       0.72      0.68      0.70      1450

    accuracy                           0.66      2537
   macro avg       0.66      0.66      0.66      2537
weighted avg       0.67      0.66      0.66      2537

AUC: 0.6611940487897725
```

Random forest on dataset reduced using forward feature selection/backward feature elimination had the highest accuracy and AUC value closest to 1.