final-project

August 18, 2024

1 Final Project - Kruanl Desai

Hello! This is my final project for *DTSA 5509 Introduction to Machine Learning: Supervised Learning.* We are utilizing data from UCI Machine Learning Repository https://archive.ics.uci.edu/

We are using Bank Marketing (with social/economic context) Data Set that has the following description: *This dataset is using "in-vehicle coupon recommendation Data Set" UCI dataset.*

With the following Attribute Information:

```
    destination: No Urgent Place, Home, Work
    passanger: Alone, Friend(s), Kid(s), Partner (who are the passengers in the car)
    weather: Sunny, Rainy, Snowy
    temperature:55, 80, 30
    time: 2PM, 10AM, 6PM, 7AM, 10PM
    coupon: Restaurant(<$20), Coffee House, Carry out & Take away, Bar, Restaurant($20-$50)
expiration: 1d, 2h (the coupon expires in 1 day or in 2 hours)
gender: Female, Male
age: 21, 46, 26, 31, 41, 50plus, 36, below21
maritalStatus: Unmarried partner, Single, Married partner, Divorced, Widowed
has_Children:1, 0
education: Some college - no degree, Bachelors degree, Associates degree, High School Graduate
occupation: Unemployed, Architecture & Engineering, Student,
Education&Training&Library, Healthcare Support,
Healthcare Practitioners & Technical, Sales & Related, Management,
Arts Design Entertainment Sports & Media, Computer & Mathematical,
Life Physical Social Science, Personal Care & Service,
Community & Social Services, Office & Administrative Support,
Construction & Extraction, Legal, Retired,
Installation Maintenance & Repair, Transportation & Material Moving,
Business & Financial, Protective Service,
Food Preparation & Serving Related, Production Occupations,
Building & Grounds Cleaning & Maintenance, Farming Fishing & Forestry
income: $37500 - $49999, $62500 - $74999, $12500 - $24999, $75000 - $87499,
$50000 - $62499, $25000 - $37499, $100000 or More, $87500 - $99999, Less than $12500
Bar: never, less1, 1~3, gt8, nan4~8 (feature meaning: how many times do you go to a bar every m
CoffeeHouse: never, less1, 4~8, 1~3, gt8, nan (feature meaning: how many times do you go to a c
CarryAway:n4~8, 1~3, gt8, less1, never (feature meaning: how many times do you get take-away fo
RestaurantLessThan20: 4~8, 1~3, less1, gt8, never (feature meaning: how many times do you go to
```

```
Restaurant20To50: 1~3, less1, never, gt8, 4~8, nan (feature meaning: how many times do you go t
toCoupon_GEQ15min:0,1 (feature meaning: driving distance to the restaurant/bar for using the co
toCoupon_GEQ25min:0, 1 (feature meaning: driving distance to the restaurant/bar for using the c
direction_same:0, 1 (feature meaning: whether the restaurant/bar is in the same direction as yo
direction_opp:1, 0 (feature meaning: whether the restaurant/bar is in the same direction as you
Y:1, 0 (whether the coupon is accepted)
```

Source: https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

Citation: [Moro et al., 2014] S. Moro, P. Cortez and P. Rita. A Data-Driven Approach to Predict the Success of Bank Telemarketing. Decision Support Systems, Elsevier, 62:22-31, June 2014

2 Project Summary

2.1 Objective

I want to use this data to help predict the conditions and personal traits for people that take coupons when they are driving past. This will help the employees of those companies to better give out those coupons and to avoid conditions where people are less likely to accept them. The data includes both personal traits, weather conditions, and range of the establishment from the place that coupons are being given out.

2.2 Main model

The main model I will use is a Data Tree Classifier as it utilizes all the features provided in the data, and will also help me to find the most important features.

Note: While deciding when and where to give out coupons the employees will not be able to have personal trait details, but given the insight into the data we will be able to at least provide them with insight into external factors.

2.3 Import Libraries and Data

We start with importing necessary libraries:

[1]:
```python
%matplotlib inline
import sklearn
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
import numpy as np
import scipy as sp
import scipy.stats as stats
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# Set color map to have light blue background
sns.set()
import statsmodels.formula.api as smf
import statsmodels.api as sm
from sklearn.tree import DecisionTreeClassifier
```

```python
from sklearn.metrics import accuracy_score, make_scorer
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import f1_score
from sklearn import tree
```

Source: https://archive.ics.uci.edu/ml/datasets/Bank+Marketing

2.3.1 Data Import

We then import the data from the data file:

[2]:
```python
df = pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/
↪00603/in-vehicle-coupon-recommendation.csv')
```

Below we see a sample of the data

[3]:
```python
df.head()
```

[3]:
```
       destination  passanger weather  temperature  time  \
0  No Urgent Place      Alone   Sunny           55   2PM
1  No Urgent Place  Friend(s)   Sunny           80  10AM
2  No Urgent Place  Friend(s)   Sunny           80  10AM
3  No Urgent Place  Friend(s)   Sunny           80   2PM
4  No Urgent Place  Friend(s)   Sunny           80   2PM

                 coupon expiration  gender age      maritalStatus  …  \
0       Restaurant(<20)         1d  Female  21  Unmarried partner  …
1          Coffee House         2h  Female  21  Unmarried partner  …
2  Carry out & Take away        2h  Female  21  Unmarried partner  …
3          Coffee House         2h  Female  21  Unmarried partner  …
4          Coffee House         1d  Female  21  Unmarried partner  …

  CoffeeHouse CarryAway RestaurantLessThan20 Restaurant20To50  \
0       never       NaN                  4~8              1~3
1       never       NaN                  4~8              1~3
2       never       NaN                  4~8              1~3
3       never       NaN                  4~8              1~3
4       never       NaN                  4~8              1~3

  toCoupon_GEQ5min toCoupon_GEQ15min toCoupon_GEQ25min direction_same  \
0                1                 0                 0              0
1                1                 0                 0              0
2                1                 1                 0              0
3                1                 1                 0              0
4                1                 1                 0              0

  direction_opp  Y
```

```
0              1  1
1              1  0
2              1  1
3              1  0
4              1  0

[5 rows x 26 columns]
```

There doesn't seem to be any NULL values but they are set to unknown

[4]:
```python
print(df.info())
df.describe()
```

```
<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
None
```

[4]:
```
       temperature  has_children  toCoupon_GEQ5min  toCoupon_GEQ15min  \
count  12684.000000  12684.000000           12684.0       12684.000000
mean      63.301798      0.414144               1.0           0.561495
std       19.154486      0.492593               0.0           0.496224
min       30.000000      0.000000               1.0           0.000000
25%       55.000000      0.000000               1.0           0.000000
50%       80.000000      0.000000               1.0           1.000000
75%       80.000000      1.000000               1.0           1.000000
max       80.000000      1.000000               1.0           1.000000

       toCoupon_GEQ25min  direction_same  direction_opp             Y
count       12684.000000    12684.000000   12684.000000  12684.000000
mean            0.119126        0.214759       0.785241      0.568433
std             0.323950        0.410671       0.410671      0.495314
min             0.000000        0.000000       0.000000      0.000000
25%             0.000000        0.000000       1.000000      0.000000
50%             0.000000        0.000000       1.000000      1.000000
75%             0.000000        0.000000       1.000000      1.000000
max             1.000000        1.000000       1.000000      1.000000
```

We initially have 25 features with 12684 rows, as we go through data cleaning this may change. Please find the description for each feature above.

2.3.2 Data Cleaning

We want to find the columns that have null values and the course of action for each.

[5]:
```
for c in df.columns:
    if(df[c].isnull().sum() / len(df) >0 and df[c].isnull().sum() / len(df) <= .
 ↪05):
        print("Impute column '",c, "'  - Percenteage of null values: ", df[c].
 ↪isnull().sum() / len(df))
    elif (df[c].isnull().sum() / len(df)) > .05:
        print("Drop column '", c, "'  - Percenteage of null values: ", df[c].
 ↪isnull().sum() / len(df))
```

```
Drop column ' car '  - Percenteage of null values:  0.9914853358561968
Impute column ' Bar '  - Percenteage of null values:  0.008435824660990224
Impute column ' CoffeeHouse '  - Percenteage of null values:
0.017108167770419427
Impute column ' CarryAway '  - Percenteage of null values:  0.011904761904761904
Impute column ' RestaurantLessThan20 '  - Percenteage of null values:
0.010249132765689057
Impute column ' Restaurant20To50 '  - Percenteage of null values:
0.014900662251655629
```

The column `car` has 99.14% missing values so it needs to be dropped as it is above the 5% acceptable null values. The rest of the columns that contain null values can be imputed with the mode of each as they are all categorical columns.

[6]:
```python
# Drop column 'car'
df = df.drop(columns=['car'])
```

[7]:
```python
#Impute the remaining columns with null values
cols = df.columns
feats_w_null = []
for c in df.columns:
    if df[c].isnull().sum() > 0:
        feats_w_null.append(c)


print(feats_w_null)
```

```
['Bar', 'CoffeeHouse', 'CarryAway', 'RestaurantLessThan20', 'Restaurant20To50']
```

[8]:
```python
#For each column in feats_w_null we get the mode and replace all null values␣
↪with the most common entry

for x in feats_w_null:
    replacement = df[x].mode()
    df[x].fillna(replacement[0], inplace=True)
    print("Filled nulls for", x)
```

```
Filled nulls for Bar
Filled nulls for CoffeeHouse
Filled nulls for CarryAway
Filled nulls for RestaurantLessThan20
Filled nulls for Restaurant20To50
```

[9]:
```python
for c in df.columns:
    if(df[c].isnull().sum() / len(df) >0 and df[c].isnull().sum() / len(df) <= .
↪05):
        print("Impute: ",c)
    elif (df[c].isnull().sum() / len(df)) > .05:
        print("Drop :", c)
```

[10]:
```python
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12684 entries, 0 to 12683
Data columns (total 25 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  Bar                   12684 non-null  object
 15  CoffeeHouse           12684 non-null  object
 16  CarryAway             12684 non-null  object
 17  RestaurantLessThan20  12684 non-null  object
 18  Restaurant20To50      12684 non-null  object
 19  toCoupon_GEQ5min      12684 non-null  int64
 20  toCoupon_GEQ15min     12684 non-null  int64
 21  toCoupon_GEQ25min     12684 non-null  int64
 22  direction_same        12684 non-null  int64
 23  direction_opp         12684 non-null  int64
 24  Y                     12684 non-null  int64
dtypes: int64(8), object(17)
memory usage: 2.4+ MB
None
```

After data cleaning, we now have no null values and 24 features with the same number of rows.

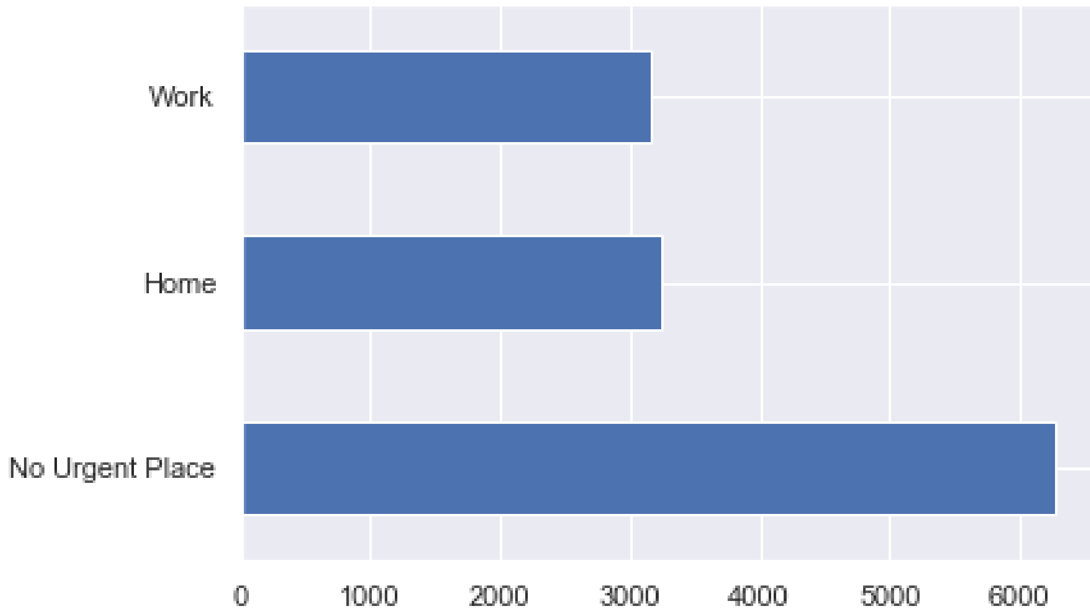
2.3.3 Data Visualization

Lets take a deeper dive into the categorical data and visualize them

Destination

[11]:
```python
df['destination'].value_counts().plot(kind='barh')
```

[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d57d423588>
```



[12]:
```
destination = df.groupby(['destination', 'Y']).size().unstack()
destination
```

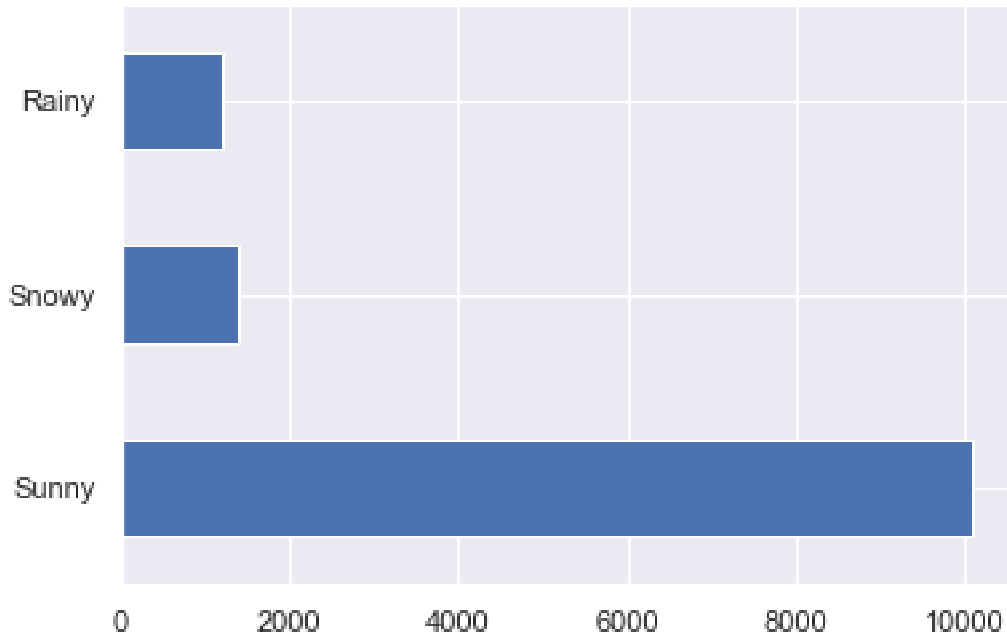
[12]:
```
Y                   0     1
destination
Home             1598  1639
No Urgent Place  2301  3982
Work             1575  1589
```

From this we can see that there is a split between "No Urgent Place" and the other two categories of "Work" and "Home". This is a good indicator that the coupons are being spread at different times of the day and during different days of the week. As well, we see almost a 50/50 split within the outcome based on the value of the persons destination.

Weather

[13]:
```
df['weather'].value_counts().plot(kind='barh')
```

[13]: <matplotlib.axes._subplots.AxesSubplot at 0x1d57d5034c8>



[14]:
```
weather = df.groupby(['weather', 'Y']).size().unstack()
weather
```

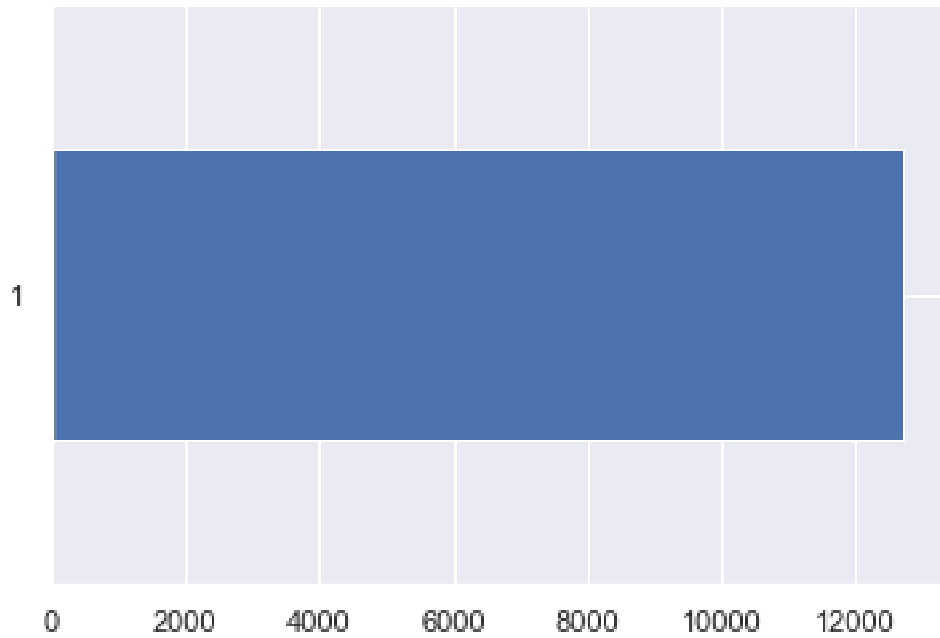
[14]:
```
Y           0     1
weather
Rainy     650   560
Snowy     744   661
Sunny    4080  5989
```

There is about a 50/50 split for people accepting the coupon based on the weather, so we can see that there is no direct correlation between the two visalized features above.

toCoupon_GEQ5min

[15]:
```
df['toCoupon_GEQ5min'].value_counts().plot(kind='barh')
```

[15]: <matplotlib.axes._subplots.AxesSubplot at 0x1d57d572188>



The values of `toCoupon_GEQ5min` are all 1 so we can drop this column as it does not provide valuable data.

```
[16]: df = df.drop(columns=['toCoupon_GEQ5min'])
```

Now we have 23 features to work with.

3 Categorical string to int

We need to change all string categorical data into integer. I utilized the LabelEncoder function in sklearn to do this instead of manually mapping each instance to a value.

```
[17]: dtypes = df.dtypes #Data Types for each column
columns = df.columns # Columns in dataframe
for x in columns:
    if dtypes[x] == object: #If the values are not continous
        print("Column:",x, '\n', " String categories:",df[x].unique()) #Print␣
 ↪old string categories
        le = preprocessing.LabelEncoder() #Init LabelEncoder
        le.fit(df[x].unique()) #Fit it with the unique values in the dataframe␣
 ↪column
        df[x] = le.transform(df[x]) #Transform them into their integer values
        print( "  Int categories:",df[x].unique()) #Print new values
```

```
Column: destination
  String categories: ['No Urgent Place' 'Home' 'Work']
```

```
  Int categories: [1 0 2]
Column: passanger
  String categories: ['Alone' 'Friend(s)' 'Kid(s)' 'Partner']
  Int categories: [0 1 2 3]
Column: weather
  String categories: ['Sunny' 'Rainy' 'Snowy']
  Int categories: [2 0 1]
Column: time
  String categories: ['2PM' '10AM' '6PM' '7AM' '10PM']
  Int categories: [2 0 3 4 1]
Column: coupon
  String categories: ['Restaurant(<20)' 'Coffee House' 'Carry out & Take away'
'Bar'
 'Restaurant(20-50)']
  Int categories: [4 2 1 0 3]
Column: expiration
  String categories: ['1d' '2h']
  Int categories: [0 1]
Column: gender
  String categories: ['Female' 'Male']
  Int categories: [0 1]
Column: age
  String categories: ['21' '46' '26' '31' '41' '50plus' '36' 'below21']
  Int categories: [0 5 1 2 4 6 3 7]
Column: maritalStatus
  String categories: ['Unmarried partner' 'Single' 'Married partner' 'Divorced'
'Widowed']
  Int categories: [3 2 1 0 4]
Column: education
  String categories: ['Some college - no degree' 'Bachelors degree' 'Associates
degree'
 'High School Graduate' 'Graduate degree (Masters or Doctorate)'
 'Some High School']
  Int categories: [5 1 0 3 2 4]
Column: occupation
  String categories: ['Unemployed' 'Architecture & Engineering' 'Student'
 'Education&Training&Library' 'Healthcare Support'
 'Healthcare Practitioners & Technical' 'Sales & Related' 'Management'
 'Arts Design Entertainment Sports & Media' 'Computer & Mathematical'
 'Life Physical Social Science' 'Personal Care & Service'
 'Community & Social Services' 'Office & Administrative Support'
 'Construction & Extraction' 'Legal' 'Retired'
 'Installation Maintenance & Repair' 'Transportation & Material Moving'
 'Business & Financial' 'Protective Service'
 'Food Preparation & Serving Related' 'Production Occupations'
 'Building & Grounds Cleaning & Maintenance' 'Farming Fishing & Forestry']
  Int categories: [24  0 22  7 11 10 21 15  1  5 14 17  4 16  6 13 20 12 23  3
19  9 18  2
```

```
  8]
Column: income
  String categories: ['$37500 - $49999' '$62500 - $74999' '$12500 - $24999'
'$75000 - $87499'
 '$50000 - $62499' '$25000 - $37499' '$100000 or More' '$87500 - $99999'
 'Less than $12500']
  Int categories: [3 5 1 6 4 2 0 7 8]
Column: Bar
  String categories: ['never' 'less1' '1~3' 'gt8' '4~8']
  Int categories: [4 3 0 2 1]
Column: CoffeeHouse
  String categories: ['never' 'less1' '4~8' '1~3' 'gt8']
  Int categories: [4 3 1 0 2]
Column: CarryAway
  String categories: ['1~3' '4~8' 'gt8' 'less1' 'never']
  Int categories: [0 1 2 3 4]
Column: RestaurantLessThan20
  String categories: ['4~8' '1~3' 'less1' 'gt8' 'never']
  Int categories: [1 0 3 2 4]
Column: Restaurant20To50
  String categories: ['1~3' 'less1' 'never' 'gt8' '4~8']
  Int categories: [0 3 4 2 1]
```

[18]:
```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12684 entries, 0 to 12683
Data columns (total 24 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   destination           12684 non-null  int32
 1   passanger             12684 non-null  int32
 2   weather               12684 non-null  int32
 3   temperature           12684 non-null  int64
 4   time                  12684 non-null  int32
 5   coupon                12684 non-null  int32
 6   expiration            12684 non-null  int32
 7   gender                12684 non-null  int32
 8   age                   12684 non-null  int32
 9   maritalStatus         12684 non-null  int32
 10  has_children          12684 non-null  int64
 11  education             12684 non-null  int32
 12  occupation            12684 non-null  int32
 13  income                12684 non-null  int32
 14  Bar                   12684 non-null  int32
 15  CoffeeHouse           12684 non-null  int32
 16  CarryAway             12684 non-null  int32
 17  RestaurantLessThan20  12684 non-null  int32
```

```
 18   Restaurant20To50      12684 non-null  int32
 19   toCoupon_GEQ15min     12684 non-null  int64
 20   toCoupon_GEQ25min     12684 non-null  int64
 21   direction_same        12684 non-null  int64
 22   direction_opp         12684 non-null  int64
 23   Y                     12684 non-null  int64
dtypes: int32(17), int64(7)
memory usage: 1.5 MB
None
```

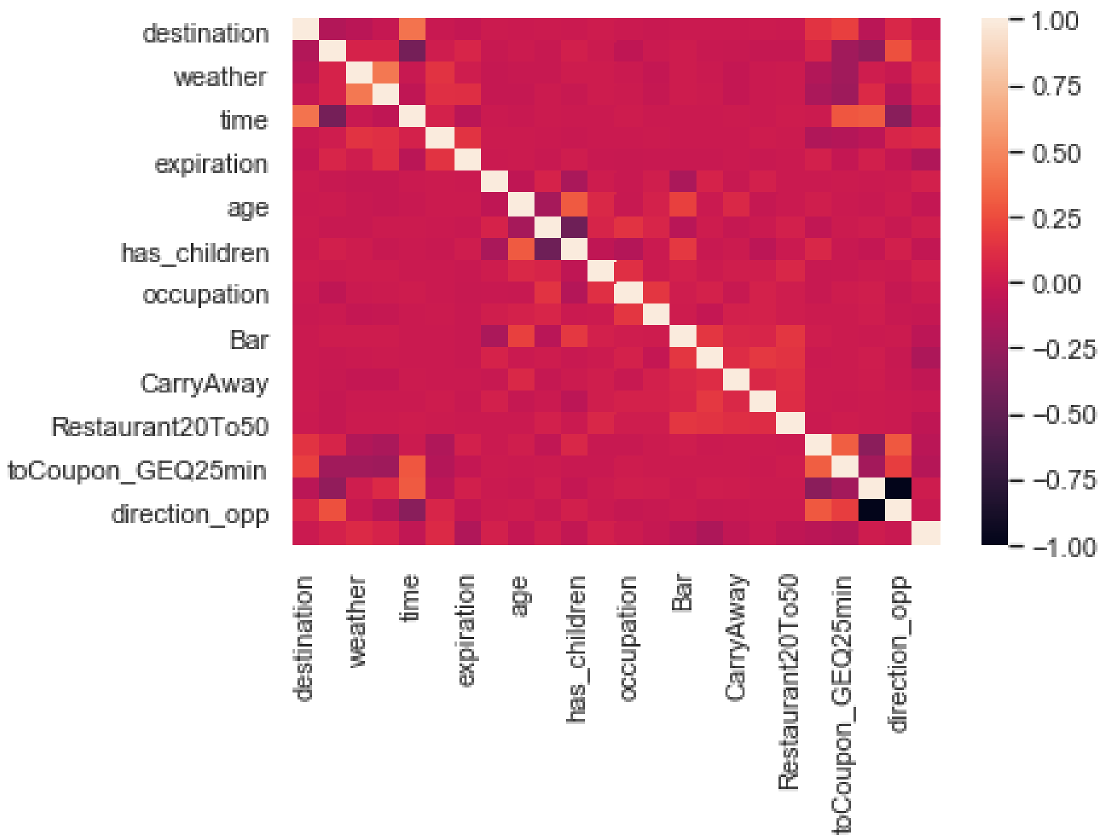
Now we have all our columns in numerical form with both continous and categorical data.

4 Data Correlation

Lets test the correlation between the data and find the most correlated feature to our result

[19]:
```
sns.heatmap(df.corr()) #Heatmap for correlations in dataframe
```

[19]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d57d266108>
```



[20]:
```
#Y is the last column/row in the correlation above, we can quantify it below:
correlation = df.corr()['Y']
print(correlation.sort_values(ascending=False))
```

```
Y                       1.000000
weather                 0.098800
coupon                  0.097019
temperature             0.061240
passanger               0.051614
gender                  0.043969
education               0.043023
maritalStatus           0.025083
direction_same          0.014570
occupation              0.007521
destination            -0.001906
RestaurantLessThan20   -0.011137
direction_opp          -0.014570
income                 -0.023949
age                    -0.035241
has_children           -0.045557
time                   -0.047377
CarryAway              -0.048717
Restaurant20To50       -0.056268
Bar                    -0.076033
toCoupon_GEQ15min      -0.081602
toCoupon_GEQ25min      -0.103633
expiration             -0.129920
CoffeeHouse            -0.144629
Name: Y, dtype: float64
```

Even the most correlated feature is not correlated enough to utilize a Linear model, but lets test it with some of the features:

[21]:
```
model = smf.ols(formula='Y ~ weather + coupon + CoffeeHouse ', data=df)

res = model.fit() #update this value according to the result
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      Y   R-squared:                       0.037
Model:                            OLS   Adj. R-squared:                  0.037
Method:                 Least Squares   F-statistic:                     164.4
Date:                Sun, 27 Feb 2022   Prob (F-statistic):          1.55e-104
Time:                        12:59:47   Log-Likelihood:                -8844.0
No. Observations:               12684   AIC:                         1.770e+04
Df Residuals:                   12680   BIC:                         1.773e+04
Df Model:                           3
```

```
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.4889      0.015     33.555      0.000       0.460       0.517
weather        0.0669      0.007      9.714      0.000       0.053       0.080
coupon         0.0309      0.003      9.551      0.000       0.025       0.037
CoffeeHouse   -0.0464      0.003    -16.520      0.000      -0.052      -0.041
==============================================================================
Omnibus:                    50921.461   Durbin-Watson:                   1.722
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1814.977
Skew:                          -0.258   Prob(JB):                         0.00
Kurtosis:                       1.220   Cond. No.                         13.6
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Above is a Linear Model for testing the highest correlated features, even then we don't have enough to predict future values based solely on `weather`, `coupon`, and `expiration`. So we need to use Decision Tree Classifier to have the best use of all features.

5 Decision Tree Classifier

First, we move the features and the result into x and y respectively

[22]:
```
#Split data into parameters and result
x = df.drop(columns='Y').copy()
y = df[['Y']].copy()

print(x.info())
# print(y.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  int32
 1   passanger             12684 non-null  int32
 2   weather               12684 non-null  int32
 3   temperature           12684 non-null  int64
 4   time                  12684 non-null  int32
 5   coupon                12684 non-null  int32
 6   expiration            12684 non-null  int32
 7   gender                12684 non-null  int32
 8   age                   12684 non-null  int32
```

```
 9   maritalStatus         12684 non-null  int32
 10  has_children          12684 non-null  int64
 11  education             12684 non-null  int32
 12  occupation            12684 non-null  int32
 13  income                12684 non-null  int32
 14  Bar                   12684 non-null  int32
 15  CoffeeHouse           12684 non-null  int32
 16  CarryAway             12684 non-null  int32
 17  RestaurantLessThan20  12684 non-null  int32
 18  Restaurant20To50      12684 non-null  int32
 19  toCoupon_GEQ15min     12684 non-null  int64
 20  toCoupon_GEQ25min     12684 non-null  int64
 21  direction_same        12684 non-null  int64
 22  direction_opp         12684 non-null  int64
dtypes: int32(17), int64(6)
memory usage: 1.4 MB
None
```

Then we provide a 80/20 split for trainging and testing data

[23]:
```python
#Split data into training and testing
x_train, x_test, y_train, y_test = train_test_split(x, y, train_size=0.8)
```

[24]:
```python
x_train
```

[24]:
```
       destination  passanger  weather  temperature  time  coupon  expiration  \
10425            1          0        2           80     0       2           1
6838             2          0        2           55     4       2           0
1811             1          1        2           80     0       1           1
8112             1          1        1           30     1       1           0
2286             0          0        2           80     3       2           1
…             …        …      …            …    …      …       …
7278             0          0        2           80     3       0           1
8682             1          0        2           80     0       2           0
6579             2          0        2           80     4       1           0
2649             1          1        2           80     0       1           1
9964             2          0        0           55     4       0           0

       gender  age  maritalStatus  …  income  Bar  CoffeeHouse  CarryAway  \
10425       0    0              2  …       8    0            1          2
6838        1    1              1  …       4    4            3          3
1811        0    6              1  …       4    4            3          1
8112        0    4              1  …       5    4            3          3
2286        0    4              2  …       2    3            3          3
…        …   …            …   …      …   …        …         …
7278        0    1              1  …       3    3            0          0
8682        1    1              2  …       0    1            0          3
6579        0    4              1  …       5    1            0          1
```

```
2649          0    1              1  ...       3    4            0          0
9964          1    2              2  ...       4    4            4          0

       RestaurantLessThan20  Restaurant20To50  toCoupon_GEQ15min  \
10425                     2                 1                  1
6838                      0                 3                  1
1811                      0                 3                  1
8112                      3                 3                  1
2286                      3                 4                  0
...                     ...               ...                ...
7278                      0                 0                  0
8682                      0                 3                  0
6579                      2                 3                  1
2649                      0                 3                  1
9964                      0                 0                  1

       toCoupon_GEQ25min  direction_same  direction_opp
10425                  0               0              1
6838                   1               0              1
1811                   0               0              1
8112                   0               0              1
2286                   0               0              1
...                  ...             ...            ...
7278                   0               1              0
8682                   0               0              1
6579                   1               0              1
2649                   0               0              1
9964                   1               0              1

[10147 rows x 23 columns]
```

With the data ready, we can then run random parameters on the DTC and view the accuracy score

[25]:
```python
#Decision Tree Classifier with random initial parameters
classifier = DecisionTreeClassifier(max_depth=10, random_state=14)
classifier.fit(x_train, y_train)
pred = classifier.predict(x_test)
acc_score = accuracy_score(y_true=y_test, y_pred = pred)

print("Accuracy Score for initial DTC:", acc_score)
```

```
Accuracy Score for initial DTC: 0.6988569176192353
```

An accuracy score of 69% is nice for random initial values but we can get a better score by modifying our parameters, we can run GridSearchCV to search for the best values to give us the best Accuracy of the model

[26]:
```
parameters = {'max_depth' : np.arange(3,10),
              'criterion': ['gini', 'entropy'],
               'max_leaf_nodes' : [5,10,15,20,50,100],
               'min_samples_split' : [2,4,5,10,15,20]
              }
grid_search_tree = GridSearchCV(DecisionTreeClassifier(), parameters,␣
 ↪scoring="accuracy")

grid_search_tree.fit(x_train, y_train)

print("Best Estimator values:", grid_search_tree.best_estimator_)

print('Best Score:', np.abs(grid_search_tree.best_score_))
```

```
Best Estimator values: DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,
criterion='gini',
                       max_depth=9, max_features=None, max_leaf_nodes=50,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=4,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
Best Score: 0.703360387679145
```

With the best parameters provided to us above, we can then use that model to predict the test data and get the accuracy score

[27]:
```
#Testing the best scoring parameters from above with test value:

classifier = DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,␣
 ↪criterion='gini',
                       max_depth=9, max_features=None, max_leaf_nodes=100,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=15,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')

classifier.fit(x_train, y_train)
pred = classifier.predict(x_test)
acc_score = accuracy_score(y_true=y_test, y_pred = pred)
f_score = f1_score(y_true=y_test, y_pred=pred)
print("Accuracy Score Optimized Parameters:", acc_score)
print("F1 Score Optimized Parameters:", f_score)
```

```
Accuracy Score Optimized Parameters: 0.7067402443831297
F1 Score Optimized Parameters: 0.7544554455445543
```

With the test data we get around the same accuracy score, now lets look at the most important features below:

[28]:

```
#Feature importance
features = x.columns
scores = classifier.feature_importances_.tolist()
res = pd.DataFrame({'features' : features, 'score': scores})
res = res.sort_values(by=['score'], ascending=False)
print(res)
```

```
                 features     score
5                  coupon  0.347327
15            CoffeeHouse  0.109266
14                    Bar  0.103968
6              expiration  0.062684
20      toCoupon_GEQ25min  0.056601
4                    time  0.056093
12             occupation  0.031918
1               passanger  0.028708
8                     age  0.026906
2                 weather  0.024478
0             destination  0.018712
16              CarryAway  0.017685
11              education  0.017166
22          direction_opp  0.012829
18       Restaurant20To50  0.012582
13                 income  0.011891
9           maritalStatus  0.011762
19      toCoupon_GEQ15min  0.010839
3             temperature  0.010837
17   RestaurantLessThan20  0.010641
7                  gender  0.008672
10           has_children  0.005752
21         direction_same  0.002681
```

We can thus conclude that the most important identifier from the Decision Tree Classifier model is the type of coupon that is presented to the customer, the frequency the person accepting the coupon goes to a Coffe House within a month, and if the driving time to the establishment is >=25 minutes.

We can see how our models accuracy will be if we choose the top 1, 2, 3 features provided above.

[29]:

```
#models with top 1, 2, & 3 features
top_1 = df[['coupon']].copy()
top_2 = df[['coupon', 'Bar']].copy()
top_3 = df[['coupon', 'Bar', 'income']].copy()

x_train_1, x_test_1, y_train_1, y_test_1 = train_test_split(top_1,y, test_size=.
 ↪2)
x_train_2, x_test_2, y_train_2, y_test_2 = train_test_split(top_2,y, test_size=.
 ↪2)
```

```
x_train_3, x_test_3, y_train_3, y_test_3 = train_test_split(top_3,y, test_size=.
↪2)

classifier.fit(x_train_1, y_train_1)
pred1 = classifier.predict(x_test_1)
acc_score1 = accuracy_score(y_true=y_test_1, y_pred = pred1)
print("With the top (1) feature, accuracy score = ", acc_score1)

classifier.fit(x_train_2, y_train_2)
pred2 = classifier.predict(x_test_2)
acc_score2 = accuracy_score(y_true=y_test_2, y_pred = pred2)
print("With the top (2) features, accuracy score = ", acc_score2)

classifier.fit(x_train_3, y_train_3)
pred3 = classifier.predict(x_test_3)
acc_score3 = accuracy_score(y_true=y_test_3, y_pred = pred3)
print("With the top (3) features, accuracy score = ", acc_score3)
```

```
With the top (1) feature, accuracy score =  0.6117461568782026
With the top (2) features, accuracy score =  0.6318486401261332
With the top (3) features, accuracy score =  0.6314544737879385
```

Accuracy fluctuates with the addition of additional parameters. But, there is an increase in accuracy as we add more features.

5.1 Confusion Matrix

For the optimized DTC model we created above, we want to view how we can improve the values of FN and FP. First lets view the amounts for those:

[30]:
```
#Confusion Matrix
cm = sklearn.metrics.confusion_matrix(y_test, pred)
print(cm)

TP = 0
FP = 0
TN = 0
FN = 0

y_true = y_test.values.tolist()
pos_label_value = 1
for l in range(len(pred)):
    predicted = pred[l]
    true = y_true[l][0]
    if predicted == pos_label_value and true == pos_label_value:
        TP += 1
    elif predicted == pos_label_value and true != pos_label_value:
        FP += 1
```

```
    elif predicted != pos_label_value and true == pos_label_value:
        FN += 1
    elif predicted != pos_label_value and true != pos_label_value:
        TN += 1
print("TP = ", TP)
print("FP = ", FP)
print("TN = ", TN)
print("FN = ", FN)
```

```
[[ 650  481]
 [ 263 1143]]
TP =  1143
FP =  481
TN =  650
FN =  263
```

To improve those amounts we can change the GridSearchCV scoring to f1 instaed of accuracy to the predictions. This should help us to predict the TP and TN values a bit better.

[31]:
```
parameters = {'max_depth' : np.arange(3,10),
              'criterion': ['gini', 'entropy'],
               'max_leaf_nodes' : [5,10,15,20,50,100],
               'min_samples_split' : [2,4,5,10,15,20]
              }
grid_search_tree = GridSearchCV(DecisionTreeClassifier(), parameters,␣
 ↪scoring="f1")

grid_search_tree.fit(x_train, y_train)

print("Best Estimator values:", grid_search_tree.best_estimator_)

print('Best Score:', np.abs(grid_search_tree.best_score_))
```

```
Best Estimator values: DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,
criterion='gini',
                       max_depth=9, max_features=None, max_leaf_nodes=50,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
Best Score: 0.7582991914429948
```

[32]:
```
classifier = DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,␣
 ↪criterion='gini',
                       max_depth=7, max_features=None, max_leaf_nodes=50,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
```

```
                        random_state=None, splitter='best')

classifier.fit(x_train, y_train)
pred = classifier.predict(x_test)
acc_score = accuracy_score(y_true=y_test, y_pred = pred)
f_score = f1_score(y_true=y_test, y_pred=pred)
print("Accuracy Score Optimized Parameters:", acc_score)
print("F1 Score Optimized Parameters:", f_score)
```

```
Accuracy Score Optimized Parameters: 0.7027985810011825
F1 Score Optimized Parameters: 0.7438858695652175
```

[33]:
```
features = x_train.columns
scores = classifier.feature_importances_.tolist()
res = pd.DataFrame({'features' : features, 'score': scores})
res = res.sort_values(by=['score'], ascending=False)
print(res)
```

```
                features     score
5                 coupon  0.412034
15           CoffeeHouse  0.125124
14                   Bar  0.112173
6             expiration  0.072073
20      toCoupon_GEQ25min  0.065174
4                   time  0.059458
2                weather  0.026413
1              passanger  0.021995
0            destination  0.018767
8                    age  0.016942
12            occupation  0.016614
22         direction_opp  0.010436
18       Restaurant20To50  0.007535
19      toCoupon_GEQ15min  0.007071
11             education  0.006977
10          has_children  0.006916
7                 gender  0.005908
13                income  0.004732
9          maritalStatus  0.003658
16             CarryAway  0.000000
17  RestaurantLessThan20  0.000000
3            temperature  0.000000
21        direction_same  0.000000
```

[34]:
```
#Confusion Matrix
cm = sklearn.metrics.confusion_matrix(y_test, pred)
print(cm)
```

```python
TP_new = 0
FP_new = 0
TN_new = 0
FN_new = 0

y_true = y_test.values.tolist()
pos_label_value = 1
for x in range(len(pred)):
    predicted = pred[x]
    true = y_true[x][0]
    if predicted == pos_label_value and true == pos_label_value:
        TP_new += 1
    elif predicted == pos_label_value and true != pos_label_value:
        FP_new += 1
    elif predicted != pos_label_value and true == pos_label_value:
        FN_new += 1
    elif predicted != pos_label_value and true != pos_label_value:
        TN_new += 1
print("New TP = ", TP_new)
print("New FP = ", FP_new)
print("New TN = ", TN_new)
print("New FN = ", FN_new)
```

```
[[ 688  443]
 [ 311 1095]]
New TP =  1095
New FP =  443
New TN =  688
New FN =  311
```

To compare those values we can see the following:

TP = 1136, New TP = 1159

FP = 423, New FP = 467

TN = 649, New TN = 605

FN = 329, New FN = 306

Both False Negatives and true Negatives decreased, while False Positives and True Positives increased. This may be a favorable for this model and dataset as we prefer to include more people into positive to provide them with the ability to accept the coupon despite them being a possible negative as they may be persuaded by further external factors not included in this dataset.

5.1.1 Feature Engineering

For this I want to remove all personal traits, and focus on observable features.

I will start with combining direction_opp and direction_same into one column with different values:

[35]:
```
fe_df = df.copy()
fe_df['direction'] = 0
fe_df.loc[((fe_df.direction_opp == 1) & (fe_df.direction_same == 0)),␣
↪'direction'] = 0 # Opposite direction
fe_df.loc[((fe_df.direction_opp == 0) & (fe_df.direction_same == 1)),␣
↪'direction'] = 1 # Same direction
fe_df = fe_df.drop(columns=['direction_same', 'direction_opp'])
```

Next we will make the passenger column to be a binary, to make it more of an observable feature:

[36]:
```
fe_df['b_passanger'] = 0
fe_df.loc[((fe_df['passanger'] == 0), 'b_passanger')] = 0
fe_df.loc[((fe_df['passanger'] == 1) | (fe_df['passanger'] == 2) |␣
↪(fe_df['passanger'] == 3), 'b_passanger')] = 1
fe_df = fe_df.drop(columns=['passanger'])
fe_df = fe_df.rename(columns={'b_passanger' : 'new_passanger'})
```

Finally, we want to combine the columns `toCoupon_GEQ15min` and `toCoupon_GEQ25min`:

[37]:
```
fe_df['toCoupon'] = 0
fe_df.loc[((fe_df['toCoupon_GEQ15min'] == 0) & (fe_df['toCoupon_GEQ25min'] ==␣
↪0), 'toCoupon')] = 0 # Less than 15 mins
fe_df.loc[((fe_df['toCoupon_GEQ15min'] == 1) & (fe_df['toCoupon_GEQ25min'] ==␣
↪0), 'toCoupon')] = 1 # between 15 and 25
fe_df.loc[((fe_df['toCoupon_GEQ15min'] == 1) & (fe_df['toCoupon_GEQ25min'] ==␣
↪1), 'toCoupon')] = 2 # Greater than 25
fe_df = fe_df.drop(columns=['toCoupon_GEQ15min', 'toCoupon_GEQ25min'])
```

[38]:
```
fe_df = fe_df[['destination', 'new_passanger', 'weather', 'temperature',␣
↪'direction', 'time', 'coupon', 'expiration', 'toCoupon', 'Y']].copy()
```

[39]:
```
fe_df.head()
```

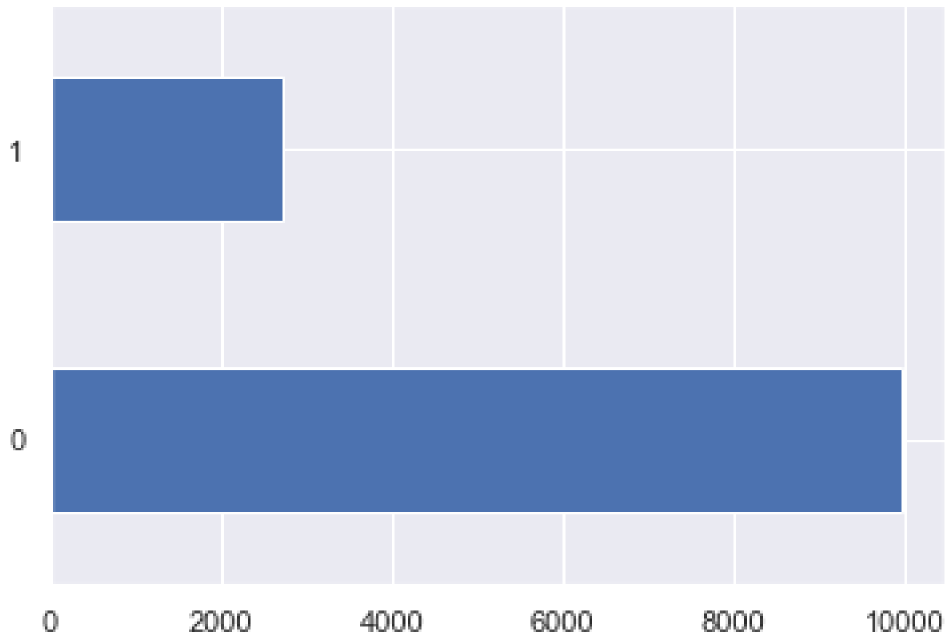
[39]:
```
   destination  new_passanger  weather  temperature  direction  time  coupon  \
0            1              0        2           55          0     2       4
1            1              1        2           80          0     0       2
2            1              1        2           80          0     0       1
3            1              1        2           80          0     2       2
4            1              1        2           80          0     2       2

   expiration  toCoupon  Y
0           0         0  1
1           1         0  0
2           1         1  1
3           1         1  0
4           0         1  0
```

5.2 Feature Engineered visualization

Lets take a look into the combined columns:

[40]:
```
fe_df['direction'].value_counts().plot(kind='barh')
```

[40]: <matplotlib.axes._subplots.AxesSubplot at 0x1d57ee187c8>



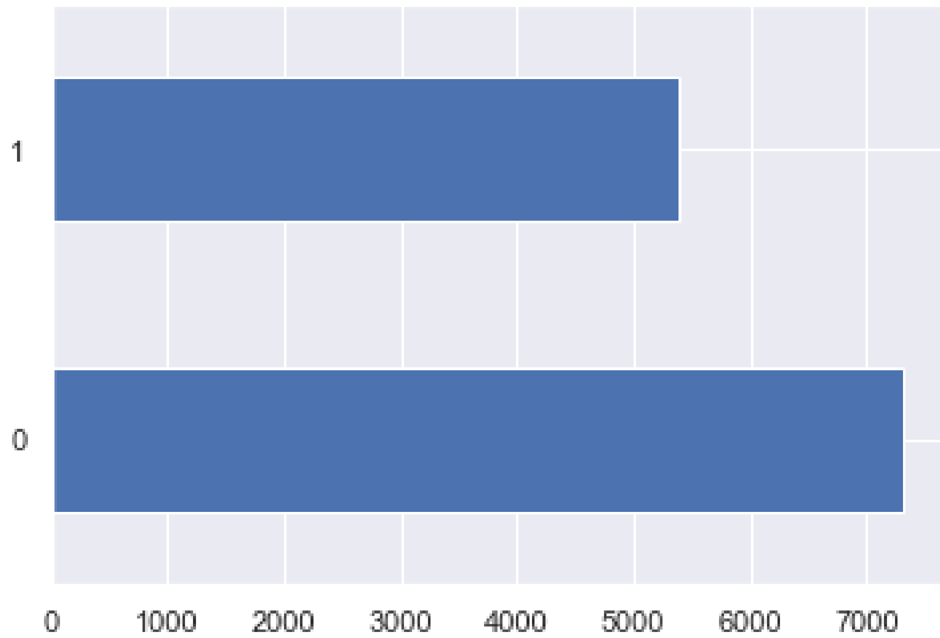
[41]:
```
direction = fe_df.groupby(['direction', 'Y']).size().unstack()
direction
```

[41]:

Y	0	1
direction		
0	4336	5624
1	1138	1586

[42]:
```
fe_df['new_passanger'].value_counts().plot(kind='barh')
```

[42]: <matplotlib.axes._subplots.AxesSubplot at 0x1d57ee8d148>



[43]:
```
passanger = fe_df.groupby(['new_passanger', 'Y']).size().unstack()
passanger
```

[43]:

Y	0	1
new_passanger		
0	3464	3841
1	2010	3369

[ ]:
```
```

5.2.1 Re-run model on new dataset

[44]:
```
fe_x = fe_df.drop(columns='Y').copy()
fe_y = fe_df[['Y']].copy()
```

[45]:
```
x_train, x_test, y_train, y_test = train_test_split(fe_x, fe_y, train_size=0.8)
```

[46]:
```
parameters = {'max_depth' : np.arange(3,10),
              'criterion': ['gini', 'entropy'],
               'max_leaf_nodes' : [5,10,15,20,50,100],
               'min_samples_split' : [2,4,5,10,15,20]
              }
grid_search_tree = GridSearchCV(DecisionTreeClassifier(), parameters,␣
 ↪scoring="accuracy")
```

```
grid_search_tree.fit(x_train, y_train)

print("Best Estimator values:", grid_search_tree.best_estimator_)

print('Best Score:', np.abs(grid_search_tree.best_score_))
```

```
Best Estimator values: DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,
criterion='gini',
                       max_depth=8, max_features=None, max_leaf_nodes=50,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
Best Score: 0.6759634074394191
```

[47]:
```
classifier = DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,␣
↪criterion='gini',
                       max_depth=9, max_features=None, max_leaf_nodes=100,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')

classifier.fit(x_train, y_train)
pred = classifier.predict(x_test)
acc_score = accuracy_score(y_true=y_test, y_pred = pred)
f_score = f1_score(y_true=y_test, y_pred=pred)
print("Accuracy Score Optimized Parameters:", acc_score)
print("F1 Score Optimized Parameters:", f_score)
```

```
Accuracy Score Optimized Parameters: 0.6665352778872684
F1 Score Optimized Parameters: 0.7183754993342211
```

[48]:
```
features = x_train.columns
scores = classifier.feature_importances_.tolist()
res = pd.DataFrame({'features' : features, 'score': scores})
res = res.sort_values(by=['score'], ascending=False)
print("Feature importance")
print(res)
```

```
Feature importance
        features     score
6         coupon  0.411138
5           time  0.148271
8       toCoupon  0.131918
7     expiration  0.128469
0    destination  0.046477
2        weather  0.040088
```

```
4      direction  0.034130
3    temperature  0.031527
1  new_passanger  0.027982
```

[49]:
```
cm = sklearn.metrics.confusion_matrix(y_test, pred)
print(cm)

fe_TP = 0
fe_FP = 0
fe_TN = 0
fe_FN = 0

y_true = y_test.values.tolist()
pos_label_value = 1
for x in range(len(pred)):
    predicted = pred[x]
    true = y_true[x][0]
    if predicted == pos_label_value and true == pos_label_value:
        fe_TP += 1
    elif predicted == pos_label_value and true != pos_label_value:
        fe_FP += 1
    elif predicted != pos_label_value and true == pos_label_value:
        fe_FN += 1
    elif predicted != pos_label_value and true != pos_label_value:
        fe_TN += 1
print("With max accuracy we get:")
print("FE Acc TP = ", fe_TP)
print("FE Acc FP = ", fe_FP)
print("FE Acc TN = ", fe_TN)
print("FE Acc FN = ", fe_FN)
```

```
[[ 612  464]
 [ 382 1079]]
With max accuracy we get:
FE Acc TP =  1079
FE Acc FP =  464
FE Acc TN =  612
FE Acc FN =  382
```

[50]:
```
parameters = {'max_depth' : np.arange(3,10),
             'criterion': ['gini', 'entropy'],
              'max_leaf_nodes' : [5,10,15,20,50,100],
              'min_samples_split' : [2,4,5,10,15,20]
             }
grid_search_tree = GridSearchCV(DecisionTreeClassifier(), parameters,␣
 ↪scoring="f1")
```

```
grid_search_tree.fit(x_train, y_train)

print("Best Estimator values:", grid_search_tree.best_estimator_)

print('Best Score:', np.abs(grid_search_tree.best_score_))
```

```
Best Estimator values: DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,
criterion='gini',
                       max_depth=8, max_features=None, max_leaf_nodes=50,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
Best Score: 0.723490490947776
```

[51]:
```
classifier = DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None,␣
 ↪criterion='entropy',
                       max_depth=6, max_features=None, max_leaf_nodes=50,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')

classifier.fit(x_train, y_train)
pred = classifier.predict(x_test)
acc_score = accuracy_score(y_true=y_test, y_pred = pred)
f_score = f1_score(y_true=y_test, y_pred=pred)
print("Accuracy Score Optimized Parameters:", acc_score)
print("F1 Score Optimized Parameters:", f_score)
```

```
Accuracy Score Optimized Parameters: 0.6610169491525424
F1 Score Optimized Parameters: 0.7172912557527943
```

[52]:
```
features = x_train.columns
scores = classifier.feature_importances_.tolist()
res = pd.DataFrame({'features' : features, 'score': scores})
res = res.sort_values(by=['score'], ascending=False)
print("Feature importance")
print(res)
```

```
Feature importance
        features     score
6         coupon  0.449976
7     expiration  0.144321
8       toCoupon  0.129089
5           time  0.110166
0    destination  0.048245
3    temperature  0.043041
```

```
4      direction  0.028011
1  new_passanger  0.027286
2        weather  0.019865
```

[53]:
```python
cm = sklearn.metrics.confusion_matrix(y_test, pred)
print(cm)

fe_TP = 0
fe_FP = 0
fe_TN = 0
fe_FN = 0

y_true = y_test.values.tolist()
pos_label_value = 1
for x in range(len(pred)):
    predicted = pred[x]
    true = y_true[x][0]
    if predicted == pos_label_value and true == pos_label_value:
        fe_TP += 1
    elif predicted == pos_label_value and true != pos_label_value:
        fe_FP += 1
    elif predicted != pos_label_value and true == pos_label_value:
        fe_FN += 1
    elif predicted != pos_label_value and true != pos_label_value:
        fe_TN += 1
print("With max f1 we get:")
print("FE f1 TP = ", fe_TP)
print("FE f1 FP = ", fe_FP)
print("FE f1 TN = ", fe_TN)
print("FE f1 FN = ", fe_FN)
```

```
[[ 586  490]
 [ 370 1091]]
With max f1 we get:
FE f1 TP =  1091
FE f1 FP =  490
FE f1 TN =  586
FE f1 FN =  370
```

Now that we only ran our model on observable features, we can see that the model improved, and will help the people passing out the coupons to use their observation skills, and decision for time and direction to pass out the coupons more effectively to people that are more likely to

[ ]:
```python

```

6 Conclusions

The model before feature engineering may not be the best even after the changes made to be more focused on f1-score rather than accuracy. But, having more positives than negatives in this situation is not the worse as it would lead to more wasted time of offering coupons to those that may not accept them, but it also will lead to more true positive outcomes.

After choosing only the obersable features we got a worse model, but unless we have a camera that views into the car and gives us the backstory and details for each person it will not be a practical model. This way we can provide those employees with the insight into what factors that they can observe to offer a coupon to a driver that is more likely to accept a coupon and improve their effeciency.

To improve this we might need to choose a different model that uses weights on each feature to have better insight into which feature will impact the customer not accepting more. I would recommend a bayesian model as well.

[ ]:

```
```