

1.Importing Libraries

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import (confusion_matrix ,ConfusionMatrixDisplay ,accuracy_score)
```

2.Loading Dataset

```
In [2]: df = pd.read_csv('Predicting Coupon Acceptance on E-commerce Platforms.csv')
```

```
In [3]: # Quick check the data
df.head()
```

```
Out[3]:
```

	destination	passanger	weather	temperature	coupon	expiration
0	No Urgent Place	Alone	Sunny	55	Restaurant(<20)	1d
1	No Urgent Place	Friend(s)	Sunny	80	Coffee House	2h
2	No Urgent Place	Friend(s)	Sunny	80	Carry out & Take away	2h
3	No Urgent Place	Friend(s)	Sunny	80	Coffee House	2h
4	No Urgent Place	Friend(s)	Sunny	80	Coffee House	1d

5 rows × 25 columns

```
In [4]: df.tail()
```

Out[4]:	destination	passanger	weather	temperature	coupon	expirati
12679	Home	Partner	Rainy	55	Carry out & Take away	
12680	Work	Alone	Rainy	55	Carry out & Take away	
12681	Work	Alone	Snowy	30	Coffee House	
12682	Work	Alone	Snowy	30	Bar	
12683	Work	Alone	Sunny	80	Restaurant(20-50)	

5 rows × 25 columns

3.Data Preprocessing

```
In [5]: # checking dataset shape
df.shape
```

Out[5]: (12684, 25)

```
In [6]: # Checking dataset size
df.size
```

Out[6]: 317100

```
In [7]: # Checking columns in dataset
df.columns
```

Out[7]: Index(['destination', 'passanger', 'weather', 'temperature', 'coupon', 'expiration', 'gender', 'age', 'maritalStatus', 'has_children', 'education', 'occupation', 'income', 'car', 'Bar', 'CoffeeHouse', 'CarryAway', 'RestaurantLessThan20', 'Restaurant20To50', 'toCoupon_GEQ5min', 'toCoupon_GEQ15min', 'toCoupon_GEQ25min', 'direction_same', 'direction_opp', 'Accept(Y/N?)'], dtype='object')

```
In [8]: # Checking the Data-Types of the Columns
df.dtypes
```

```
Out[8]: destination      object
passanger               object
weather                 object
temperature             int64
coupon                  object
expiration              object
gender                  object
age                     object
maritalStatus           object
has_children            int64
education                object
occupation              object
income                  object
car                     object
Bar                     object
CoffeeHouse             object
CarryAway                object
RestaurantLessThan20    object
Restaurant20To50        object
toCoupon_GEQ5min        int64
toCoupon_GEQ15min       int64
toCoupon_GEQ25min       int64
direction_same          int64
direction_opp           int64
Accept(Y/N?)            int64
dtype: object
```

```
In [9]: #Checking the information of the dataset
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   coupon                 12684 non-null  object
 5   expiration             12684 non-null  object
 6   gender                 12684 non-null  object
 7   age                    12684 non-null  object
 8   maritalStatus          12684 non-null  object
 9   has_children           12684 non-null  int64
10   education              12684 non-null  object
11   occupation             12684 non-null  object
12   income                 12684 non-null  object
13   car                    108 non-null    object
14   Bar                     12577 non-null  object
15   CoffeeHouse            12467 non-null  object
16   CarryAway              12533 non-null  object
17   RestaurantLessThan20   12554 non-null  object
18   Restaurant20To50       12495 non-null  object
19   toCoupon_GE05min       12684 non-null  int64
20   toCoupon_GE015min      12684 non-null  int64
21   toCoupon_GE025min      12684 non-null  int64
22   direction_same         12684 non-null  int64
23   direction_opp          12684 non-null  int64
24   Accept(Y/N?)           12684 non-null  int64
dtypes: int64(8), object(17)
memory usage: 2.4+ MB

```

```

In [10]: # is_claim Is the Target column
# Checking the value counts for number of unique values
df['Accept(Y/N?)'].value_counts()

```

```

Out[10]: Accept(Y/N?)
1      7210
0      5474
Name: count, dtype: int64

```

```

In [11]: # Checking the percentage of number of unique values are present
df['Accept(Y/N?)'].value_counts(normalize=True)*100

```

```

Out[11]: Accept(Y/N?)
1      56.843267
0      43.156733
Name: proportion, dtype: float64

```

Note1: The Target Column is Balanced

Checking Missing and Duplicate Data

```
In [12]: df.isnull().sum()
```

```
Out[12]: destination      0
passanger                0
weather                  0
temperature              0
coupon                   0
expiration               0
gender                   0
age                      0
maritalStatus            0
has_children             0
education                0
occupation               0
income                   0
car                      12576
Bar                      107
CoffeeHouse              217
CarryAway                151
RestaurantLessThan20     130
Restaurant20To50         189
toCoupon_GEQ5min         0
toCoupon_GEQ15min        0
toCoupon_GEQ25min        0
direction_same           0
direction_opp            0
Accept(Y/N?)             0
dtype: int64
```

```
In [ ]:
```

```
In [13]: df.duplicated().sum() # 291 duplicated values in datas
```

```
Out[13]: 291
```

Dropping Car col. bcz too many null values are in

```
In [14]: df.drop(columns=['car'], axis=1, inplace=True)
```

```
In [15]: 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  object
1   passanger                             12684 non-null  object
2   weather                               12684 non-null  object
3   temperature                           12684 non-null  int64
4   coupon                                12684 non-null  object
5   expiration                             12684 non-null  object
6   gender                                12684 non-null  object
7   age                                    12684 non-null  object
8   maritalStatus                         12684 non-null  object
9   has_children                          12684 non-null  int64
10  education                             12684 non-null  object
11  occupation                             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_GE05min                      12684 non-null  int64
19  toCoupon_GE015min                     12684 non-null  int64
20  toCoupon_GE025min                     12684 non-null  int64
21  direction_same                        12684 non-null  int64
22  direction_opp                         12684 non-null  int64
23  Accept(Y/N?)                          12684 non-null  int64
dtypes: int64(8), object(16)
memory usage: 2.3+ MB

```

Imputing Missing values / Handeling Missing values

```

In [16]: # Fill missing values with 'unknown' for categorical and median for numerical
for i in ['Bar', 'CoffeeHouse', 'CarryAway', 'RestaurantLessThan20', 'Restaurant20To50']:
    df[i].fillna('unknown', inplace=True)

```

```

In [17]: df.isnull().sum()

```

```

Out[17]: destination      0
passanger                0
weather                  0
temperature              0
coupon                   0
expiration               0
gender                   0
age                      0
maritalStatus            0
has_children             0
education                0
occupation               0
income                   0
Bar                       0
CoffeeHouse              0
CarryAway                 0
RestaurantLessThan20     0
Restaurant20To50         0
toCoupon_GEQ5min         0
toCoupon_GEQ15min        0
toCoupon_GEQ25min        0
direction_same           0
direction_opp             0
Accept(Y/N?)             0
dtype: int64

```

Handeling Duplicate data

```

In [18]: df.drop_duplicates(inplace=True) # Dropping duplicate values

```

```

In [19]: df.duplicated().sum() # All duplicate data handled/Drop

```

```

Out[19]: 0

```

Note 2:

Zero Missing values

Zero Duplicate values

4.Sorting Categorical and Numerical columns in list

```

In [20]: categorical=[]
numerical=[]

```

Seperating categorical column with Number of unique values

```

In [21]: for i in df.select_dtypes(include='object').columns:
print(i,":",df[i].nunique())
categorical.append(i)

```

```
print("\n\n")
print(categorical)
```

```
destination : 3
passanger : 4
weather : 3
coupon : 5
expiration : 2
gender : 2
age : 8
maritalStatus : 5
education : 6
occupation : 25
income : 9
Bar : 6
CoffeeHouse : 6
CarryAway : 6
RestaurantLessThan20 : 6
Restaurant20To50 : 6
```

```
['destination', 'passanger', 'weather', 'coupon', 'expiration', 'gender', 'age', 'maritalStatus', 'education', 'occupation', 'income', 'Bar', 'CoffeeHouse', 'CarryAway', 'RestaurantLessThan20', 'Restaurant20To50']
```

Separating Categorical and Numerical

```
In [22]: categorical = df.select_dtypes(include='O').columns.tolist()
numerical = df.select_dtypes(include=['int', 'float']).columns.tolist()

print("Categorical columns are: \n", categorical, "\n")
print("Numerical columns are: \n", numerical)
```

Categorical columns are:

```
['destination', 'passanger', 'weather', 'coupon', 'expiration', 'gender', 'age', 'maritalStatus', 'education', 'occupation', 'income', 'Bar', 'CoffeeHouse', 'CarryAway', 'RestaurantLessThan20', 'Restaurant20To50']
```

Numerical columns are:

```
['temperature', 'has_children', 'toCoupon_GEQ5min', 'toCoupon_GEQ15min', 'toCoupon_GEQ25min', 'direction_same', 'direction_opp', 'Accept(Y/N?)']
```

```
In [23]: for i in df.select_dtypes(include=['int64', 'float64']).columns:
print(i, ":", df[i].nunique())
if df[i].nunique() > 25:
    numerical.append(i)
else:
    categorical.append(i)
print("\n\n")
print(numerical)
```



```
temperature : 3
has_children : 2
toCoupon_GEQ5min : 1
toCoupon_GEQ15min : 2
toCoupon_GEQ25min : 2
direction_same : 2
direction_opp : 2
Accept(Y/N?) : 2
```

```
['temperature', 'has_children', 'toCoupon_GEQ5min', 'toCoupon_GEQ15min', 'toCoupon_GEQ25min', 'direction_same', 'direction_opp', 'Accept(Y/N?)']
```

```
In [24]: df['income'].value_counts()
```

```
Out[24]: income
$25000 - $37499      1972
$12500 - $24999      1795
$37500 - $49999      1760
$100000 or More      1688
$50000 - $62499      1624
Less than $12500     1013
$87500 - $99999       865
$75000 - $87499       844
$62500 - $74999       832
Name: count, dtype: int64
```

```
In [25]: df['income'].value_counts(normalize=True)*100
```

```
Out[25]: income
$25000 - $37499      15.912209
$12500 - $24999      14.483983
$37500 - $49999      14.201565
$100000 or More      13.620592
$50000 - $62499      13.104172
Less than $12500      8.173969
$87500 - $99999       6.979747
$75000 - $87499       6.810296
$62500 - $74999       6.713467
Name: proportion, dtype: float64
```

```
In [26]: df['occupation'].value_counts()
```

```
Out[26]: occupation
Unemployed 1828
Student 1550
Computer & Mathematical 1360
Sales & Related 1066
Education&Training&Library 921
Management 806
Office & Administrative Support 631
Arts Design Entertainment Sports & Media 617
Business & Financial 536
Retired 489
Food Preparation & Serving Related 293
Healthcare Support 237
Healthcare Practitioners & Technical 237
Community & Social Services 236
Legal 218
Transportation & Material Moving 214
Architecture & Engineering 172
Personal Care & Service 172
Protective Service 172
Life Physical Social Science 168
Construction & Extraction 150
Installation Maintenance & Repair 129
Production Occupations 108
Building & Grounds Cleaning & Maintenance 42
Farming Fishing & Forestry 41
Name: count, dtype: int64
```

```
In [27]: df['occupation'].value_counts(normalize=True)*100
```

```
Out[27]: occupation
Unemployed          14.750262
Student             12.507060
Computer & Mathematical 10.973937
Sales & Related      8.601630
Education&Training&Library 7.431615
Management          6.503671
Office & Administrative Support 5.091584
Arts Design Entertainment Sports & Media 4.978617
Business & Financial 4.325022
Retired             3.945776
Food Preparation & Serving Related 2.364238
Healthcare Support  1.912370
Healthcare Practitioners & Technical 1.912370
Community & Social Services 1.904301
Legal               1.759058
Transportation & Material Moving 1.726781
Architecture & Engineering 1.387880
Personal Care & Service 1.387880
Protective Service  1.387880
Life Physical Social Science 1.355604
Construction & Extraction 1.210361
Installation Maintenance & Repair 1.040910
Production Occupations 0.871460
Building & Grounds Cleaning & Maintenance 0.338901
Farming Fishing & Forestry 0.330832
Name: proportion, dtype: float64
```

Income group of 2500-37499 Has highest accept For yes

Similarly for lowest accept for yes And for no as well

In []:

In []:

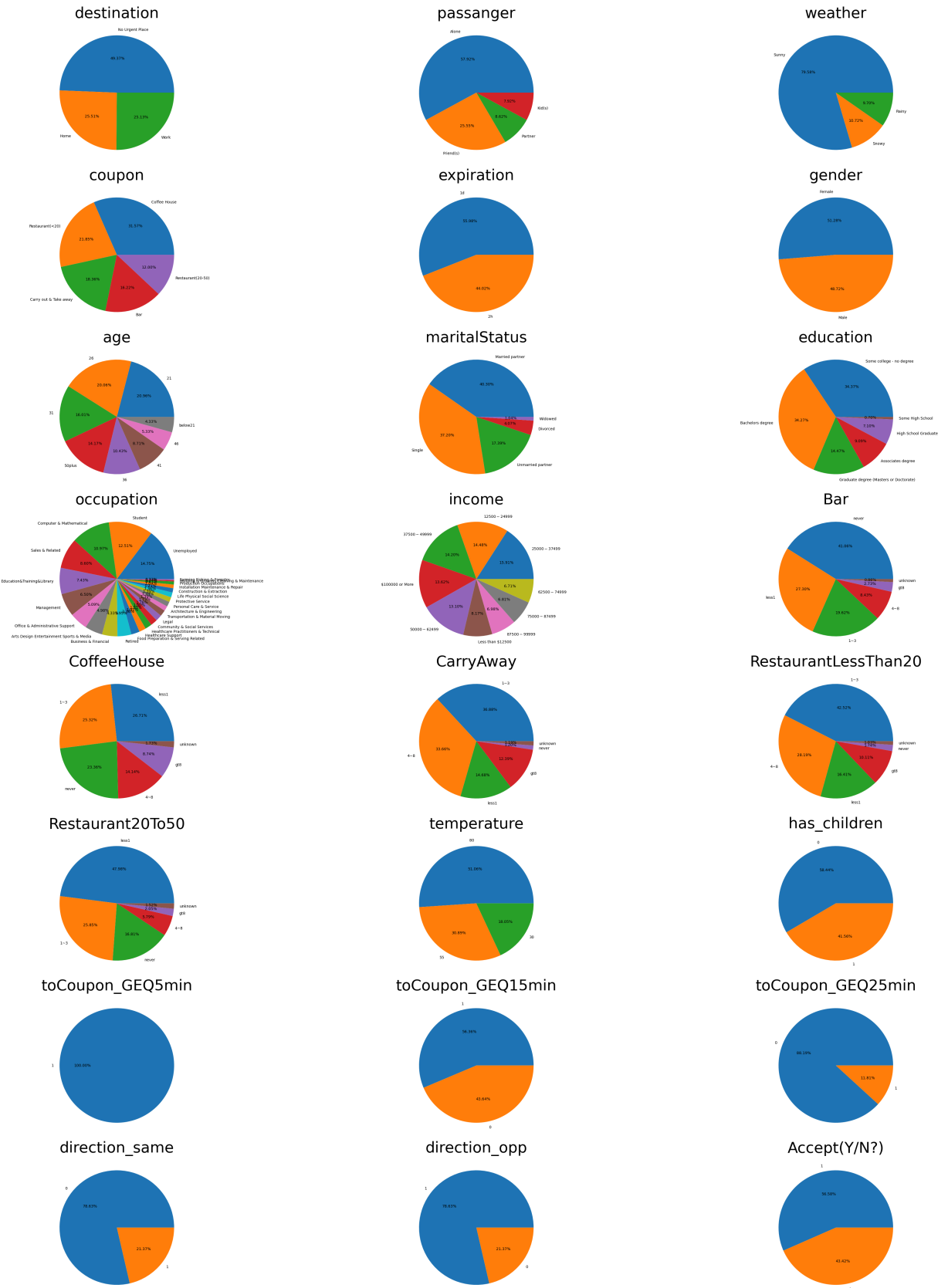
5 Exploratory Data Analysis(EDA)

A] Categorical EDA

Pie chart

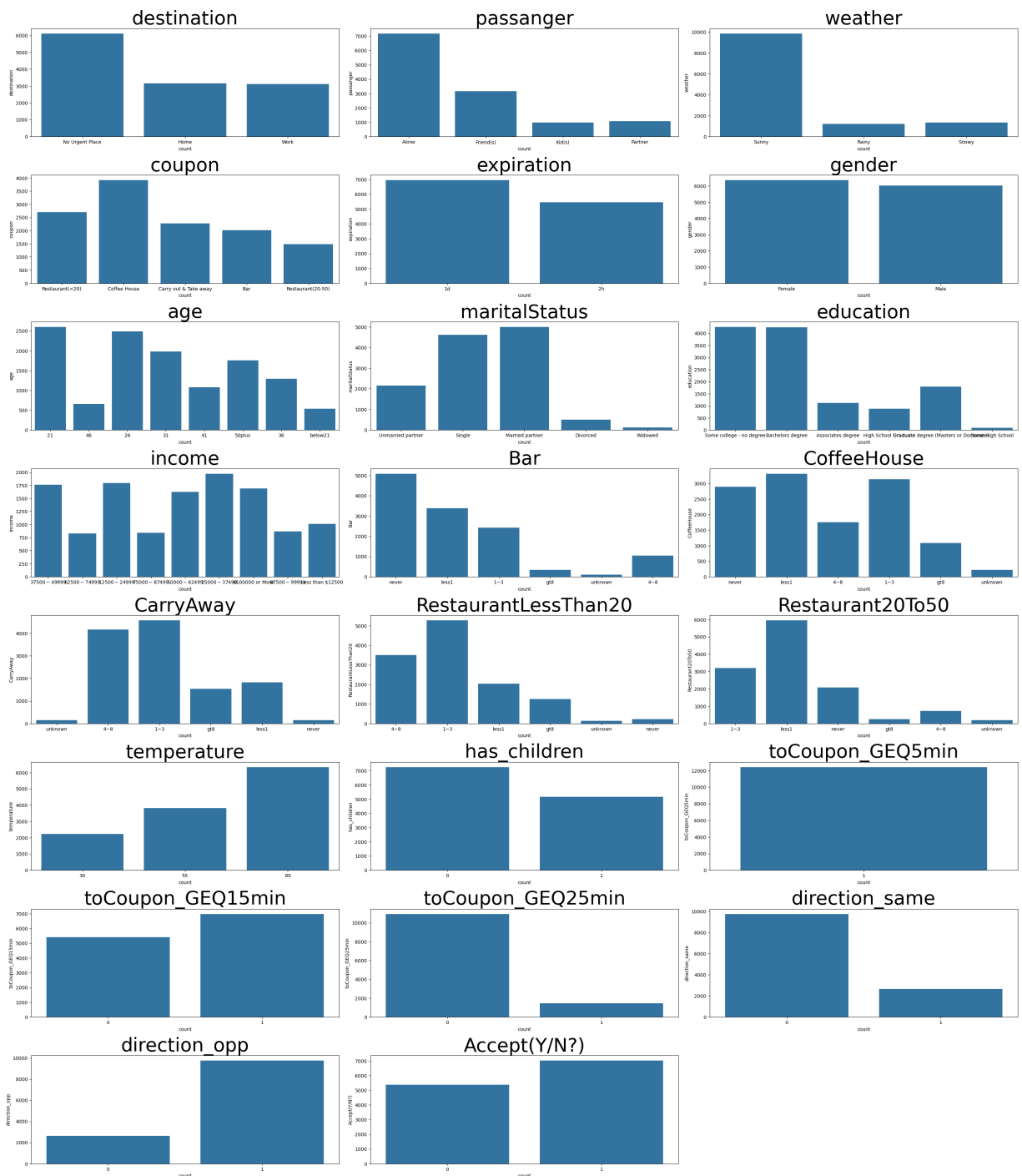
```
In [28]: fig=plt.figure(figsize=(40,90))
count=1
for i in categorical:
    if df[i].nunique():
        keys=df[i].value_counts().keys()
        values=df[i].value_counts().values
        plt.subplot(15,3,count)
        plt.pie(x=values, labels=keys, autopct='%0.2f%%')
        plt.title(i, fontsize=40)
```

```
fig.tight_layout()
count+=1
plt.show()
```



Count Plot

```
In [29]: # Example countplot for a single categorical variable
count=1
fig=plt.figure(figsize=(30,60))
for i in categorical:
    if df[i].nunique()<25:
        plt.subplot(14,3,count)
        sns.countplot(x=i, data=df,)
        plt.title(i, fontsize=40)
        plt.xlabel('count')
        plt.ylabel(i)
        fig.tight_layout()
        count+=1
plt.show()
```



In []:

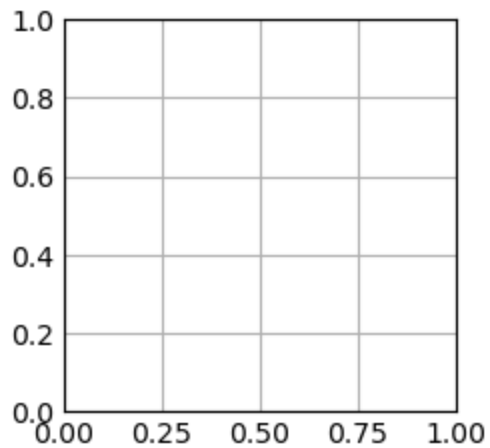
Stem plot

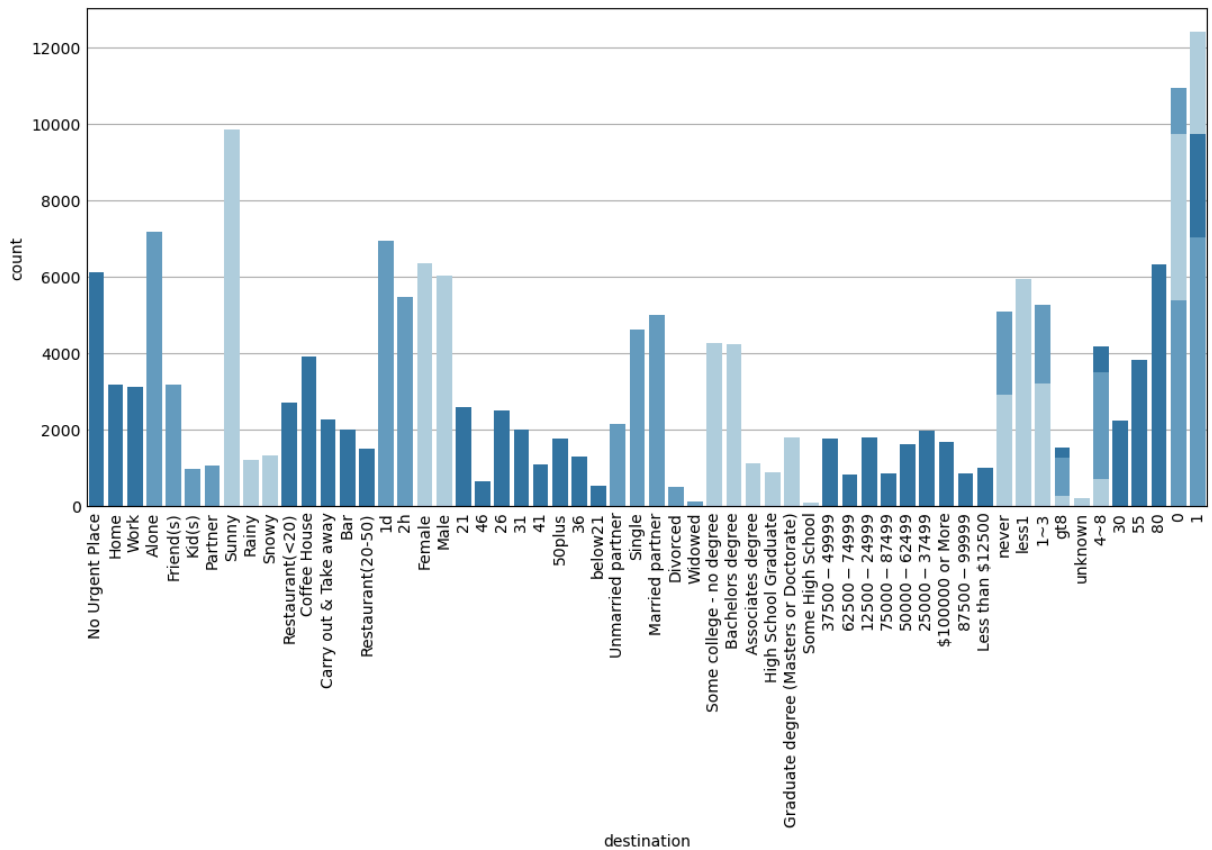
```
In [30]: plt.style.use('_mpl-gallery')

# make data
#x = 0.5 + np.arange(8)
#y = [4.8, 5.5, 3.5, 4.6, 6.5, 6.6, 2.6, 3.0]

# plot
fig, ax = plt.subplots()
count=1
fig=plt.figure(figsize=(120,140))
for i in categorical:
    if df[i].nunique() <=11:
        plt.subplot(26,10,count)
        sns.countplot(x=i, data=df,)
        plt.xticks(rotation=90)

plt.show()
```





```
In [33]: # Counting no. of unique values in every categorical columns
df[categorical].nunique()
```

```
Out[33]: destination      3
passanger                4
weather                  3
coupon                   5
expiration                2
gender                   2
age                       8
maritalStatus            5
education                 6
occupation                25
income                    9
Bar                       6
CoffeeHouse               6
CarryAway                 6
RestaurantLessThan20      6
Restaurant20To50          6
temperature               3
has_children              2
toCoupon_GEQ5min          1
toCoupon_GEQ15min         2
toCoupon_GEQ25min         2
direction_same            2
direction_opp             2
Accept(Y/N?)              2
dtype: int64
```

```
In [34]: # checking unique values of categorical columns which are less than 25
for i in categorical:
    if df[i].nunique() < 25:
        print(i, df[i].unique(), end="\n\n")
```



```

destination ['No Urgent Place' 'Home' 'Work']

passanger ['Alone' 'Friend(s)' 'Kid(s)' 'Partner']

weather ['Sunny' 'Rainy' 'Snowy']

coupon ['Restaurant(<20)' 'Coffee House' 'Carry out & Take away' 'Bar'
'Restaurant(20-50)']

expiration ['1d' '2h']

gender ['Female' 'Male']

age ['21' '46' '26' '31' '41' '50plus' '36' 'below21']

maritalStatus ['Unmarried partner' 'Single' 'Married partner' 'Divorced' 'Wi
dowed']

education ['Some college - no degree' 'Bachelors degree' 'Associates degree'
'High School Graduate' 'Graduate degree (Masters or Doctorate)'
'Some High School']

income ['$37500 - $49999' '$62500 - $74999' '$12500 - $24999' '$75000 - $874
99'
'$50000 - $62499' '$25000 - $37499' '$100000 or More' '$87500 - $99999'
'Less than $12500']

Bar ['never' 'less1' '1~3' 'gt8' 'unknown' '4~8']

CoffeeHouse ['never' 'less1' '4~8' '1~3' 'gt8' 'unknown']

CarryAway ['unknown' '4~8' '1~3' 'gt8' 'less1' 'never']

RestaurantLessThan20 ['4~8' '1~3' 'less1' 'gt8' 'unknown' 'never']

Restaurant20To50 ['1~3' 'less1' 'never' 'gt8' '4~8' 'unknown']

temperature [55 80 30]

has_children [1 0]

toCoupon_GEQ5min [1]

toCoupon_GEQ15min [0 1]

toCoupon_GEQ25min [0 1]

direction_same [0 1]

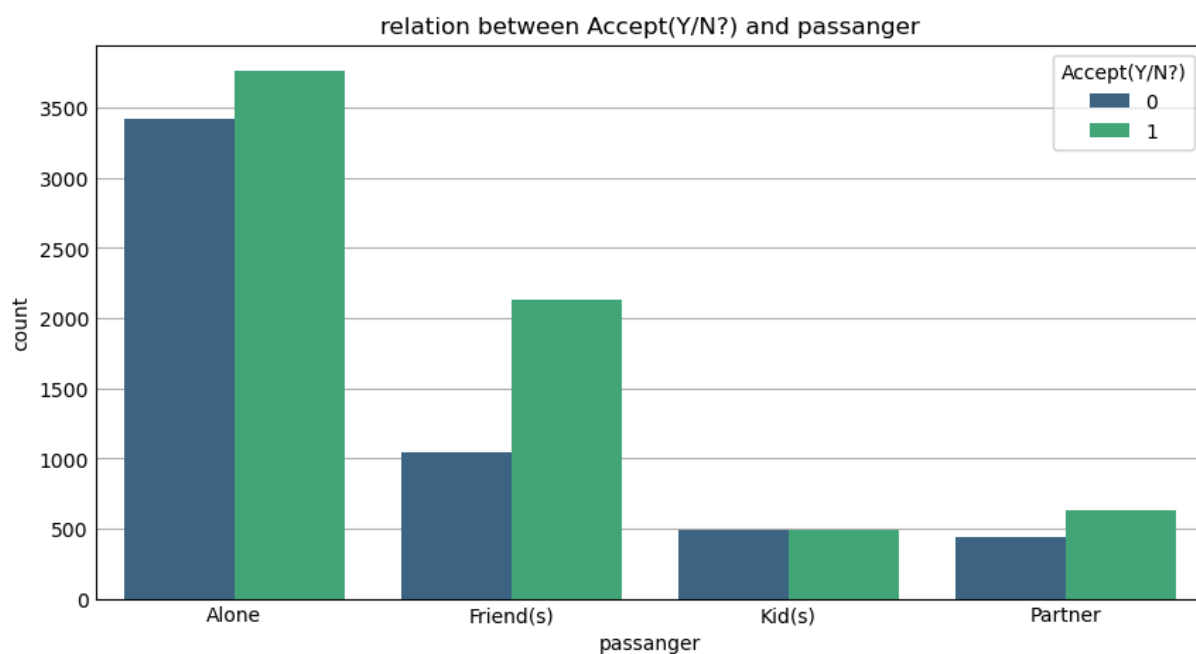
direction_opp [1 0]

Accept(Y/N?) [1 0]

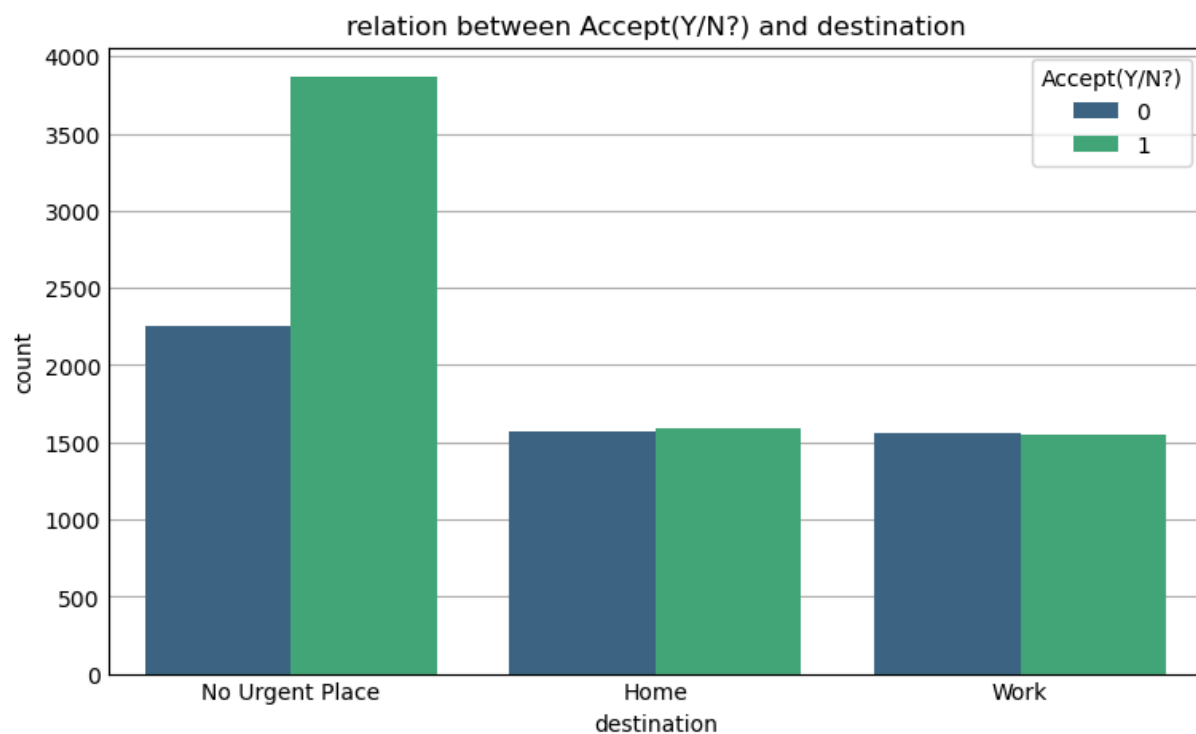
```

Count plot with hue of target column(target_col= 'Accept(Y/N?))'

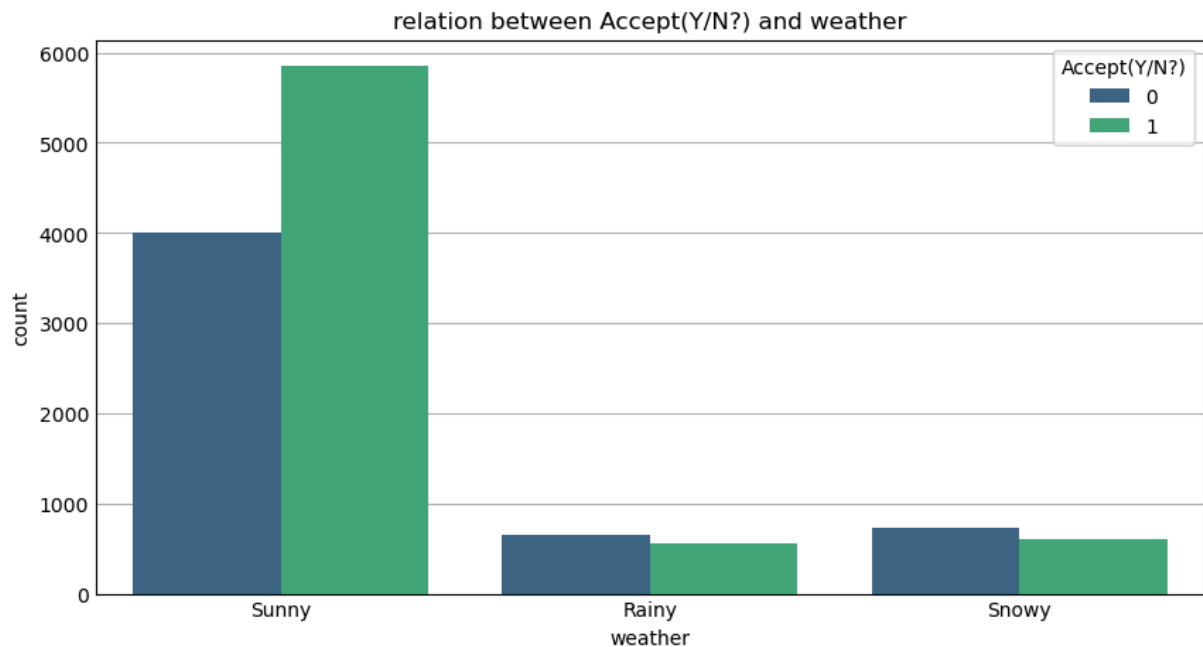
```
In [35]: # Count plot with hue of target column
plt.figure(figsize=(8,4))
sns.countplot(data = df ,x= "passanger" , hue ="Accept(Y/N?)", palette='viridis')
plt.title("relation between Accept(Y/N?) and passanger")
plt.show()
```



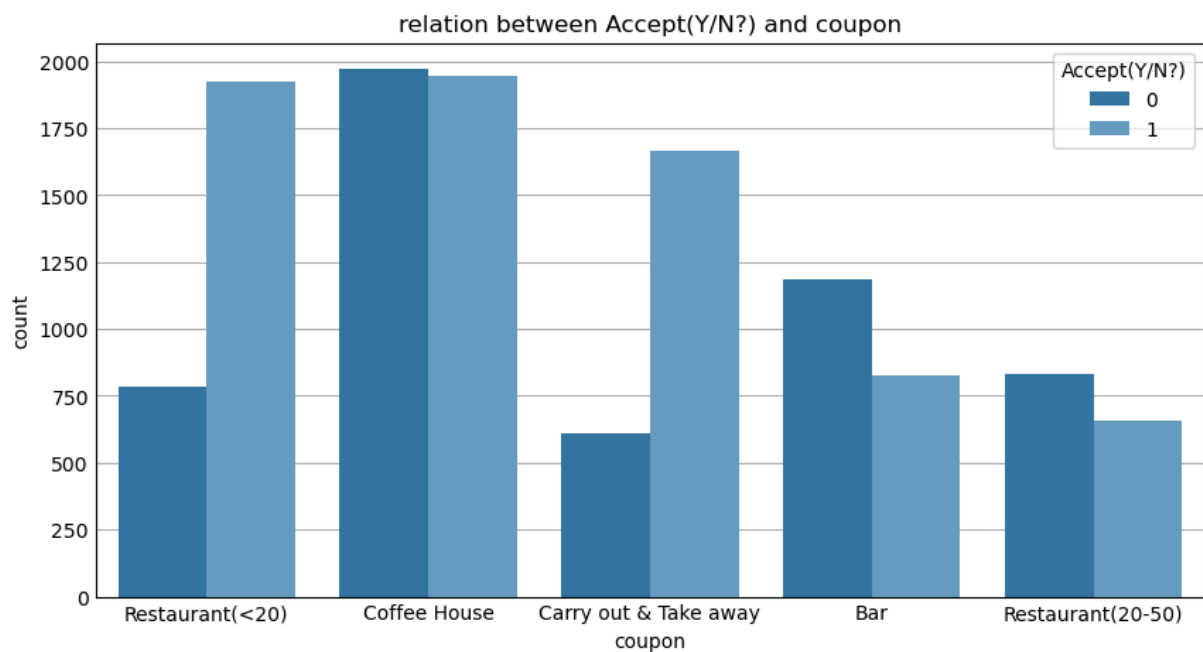
```
In [36]: plt.figure(figsize=(7,4))
sns.countplot(data = df ,x= "destination" , hue ="Accept(Y/N?)", palette='viridis')
plt.title("relation between Accept(Y/N?) and destination")
plt.show()
```



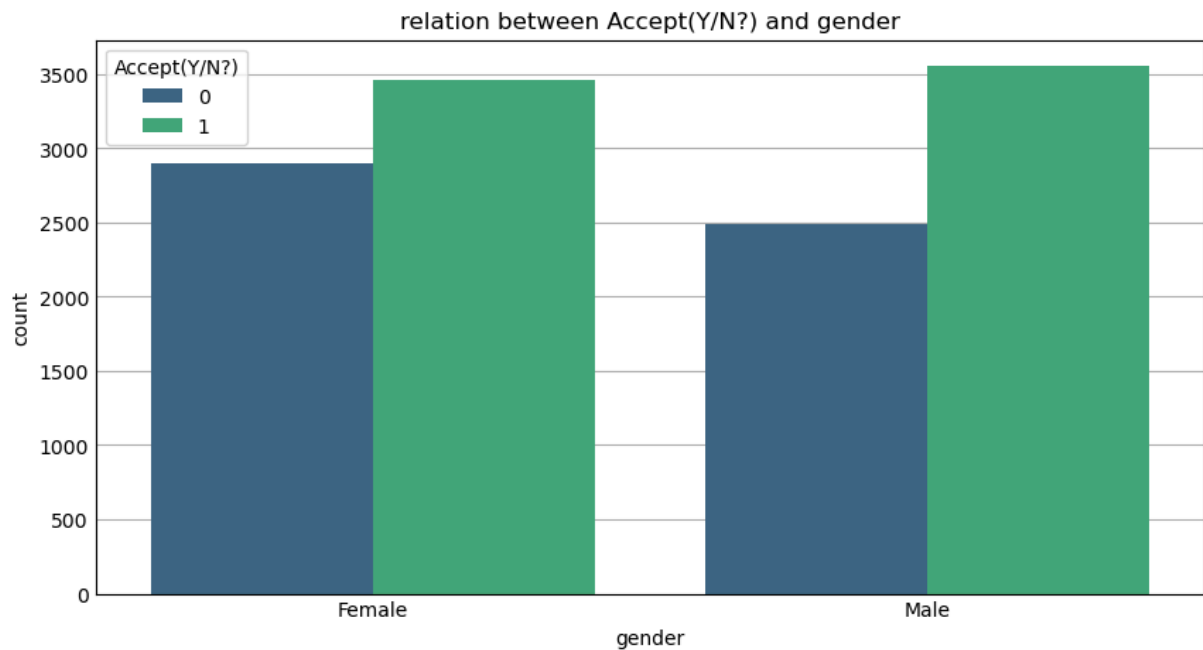
```
In [37]: plt.figure(figsize=(8,4))
sns.countplot(data = df ,x= "weather" , hue ="Accept(Y/N?)", palette='viridi
plt.title("relation between Accept(Y/N?) and weather")
plt.show()
```



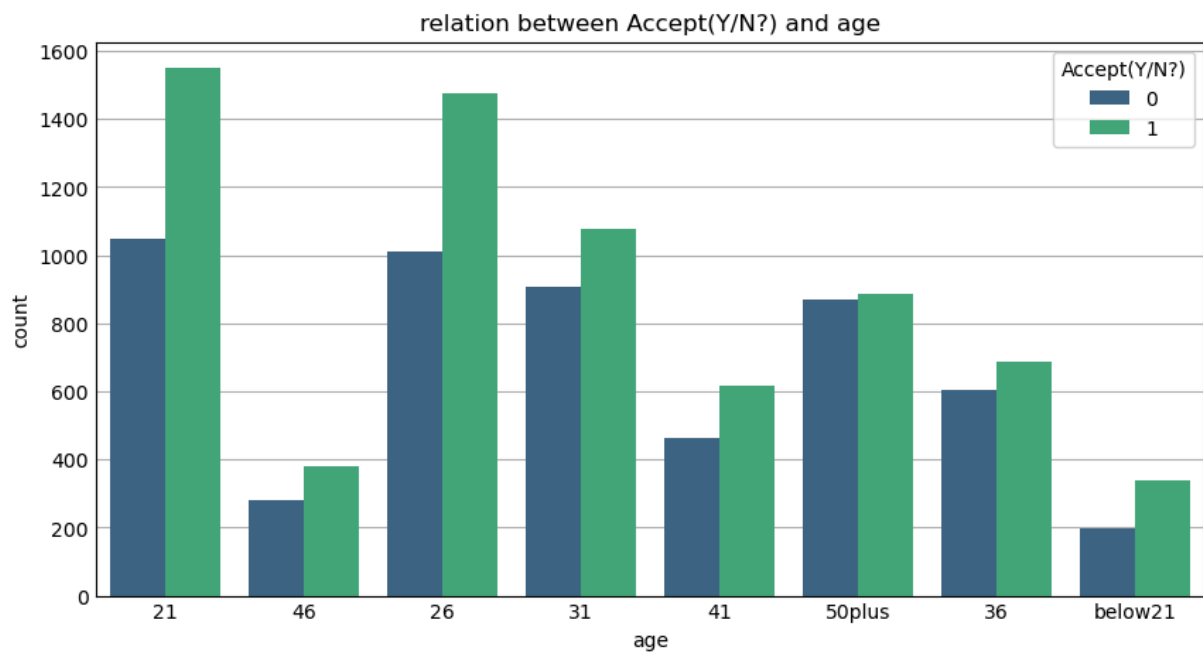
```
In [38]: plt.figure(figsize=(8,4))
sns.countplot(data = df ,x= "coupon" , hue ="Accept(Y/N?)",)
plt.title("relation between Accept(Y/N?) and coupon")
plt.show()
```



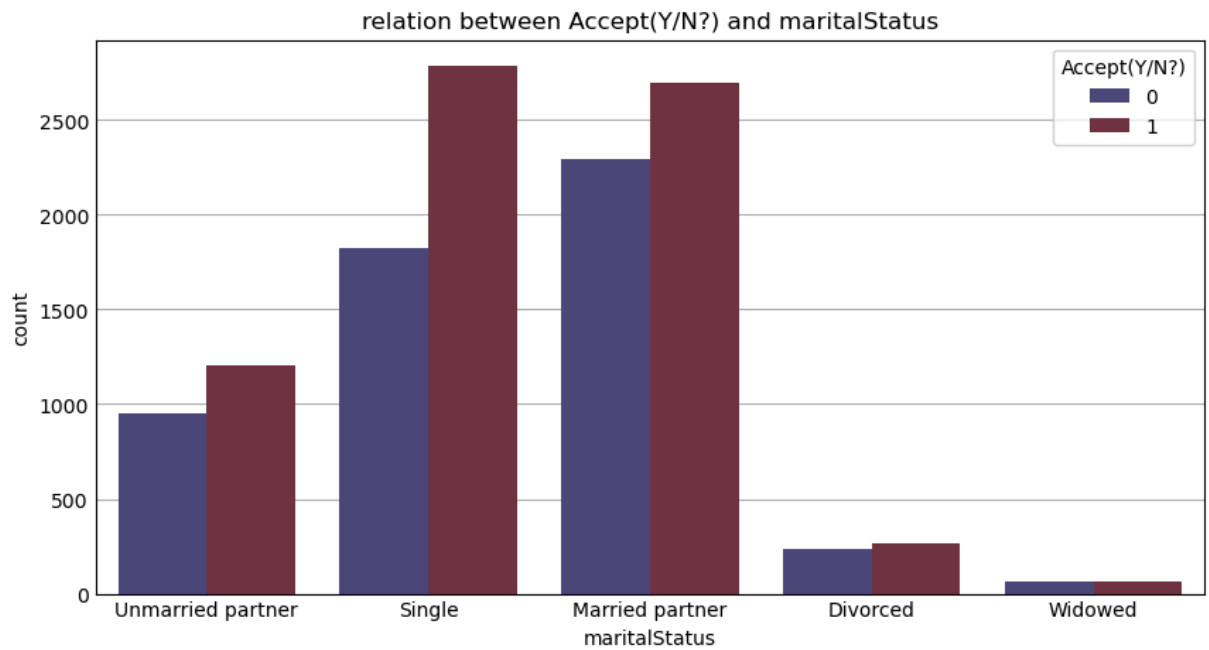
```
In [39]: plt.figure(figsize=(8,4))
sns.countplot(data = df ,x= "gender" , hue ="Accept(Y/N?)", palette='viridis
plt.title("relation between Accept(Y/N?) and gender")
plt.show()
```



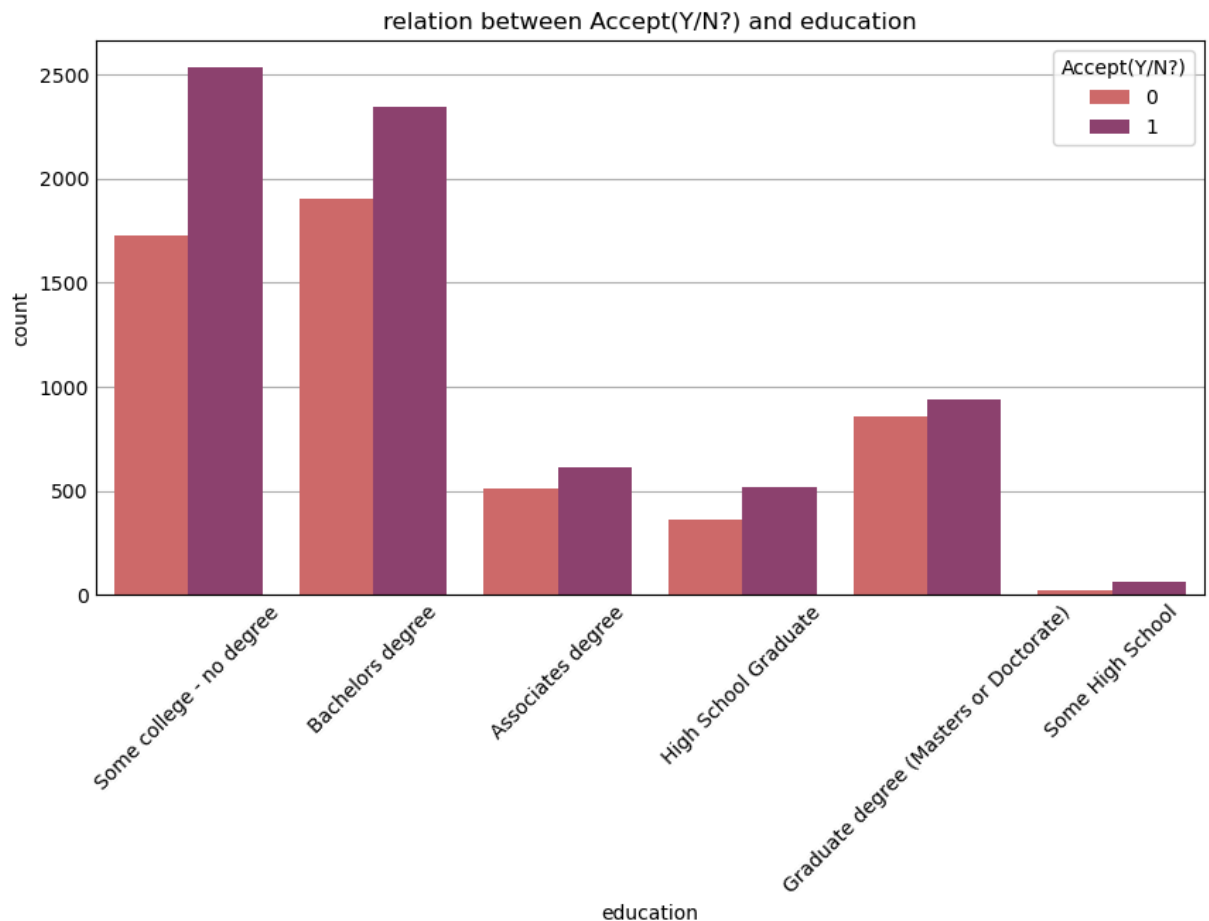
```
In [40]: plt.figure(figsize=(8,4))
sns.countplot(data = df ,x= "age" , hue ="Accept(Y/N?)", palette='viridis')
plt.title("relation between Accept(Y/N?) and age")
plt.show()
```



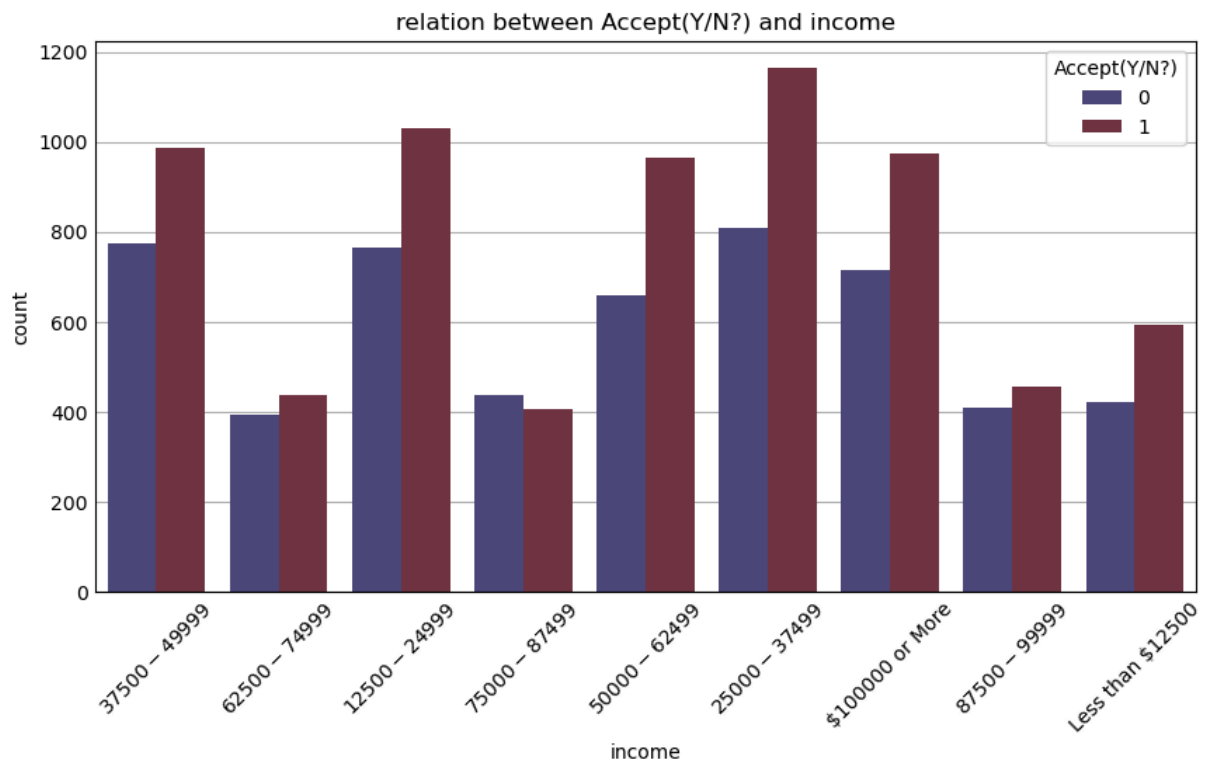
```
In [41]: plt.figure(figsize=(8,4))
sns.countplot(data = df ,x= "maritalStatus" , hue ="Accept(Y/N?)", palette='viridis')
plt.title("relation between Accept(Y/N?) and maritalStatus")
plt.show()
```



```
In [42]: plt.figure(figsize=(8,4))
sns.countplot(data = df ,x= "education" , hue ="Accept(Y/N?)", palette='flare_r')
plt.title("relation between Accept(Y/N?) and education")
plt.xticks(rotation=45)
plt.show()
```



```
In [43]: plt.figure(figsize=(8,4))
sns.countplot(data = df ,x= "income" , hue ="Accept(Y/N?)", palette='icefire')
plt.title("relation between Accept(Y/N?) and income")
plt.xticks(rotation=45)
plt.show()
```



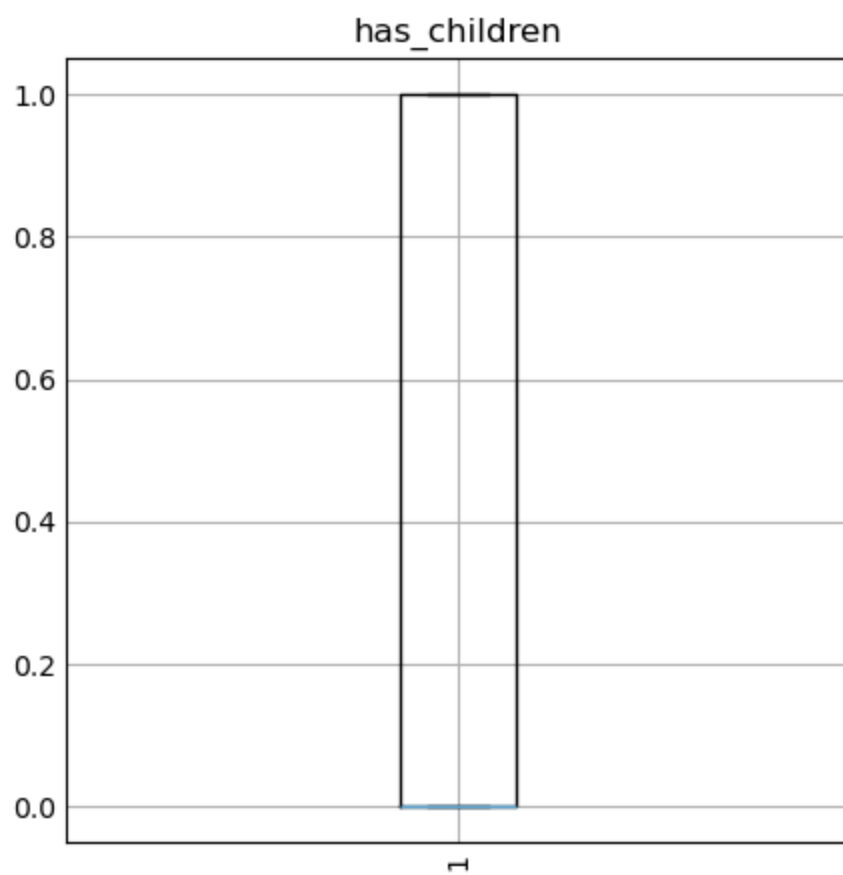
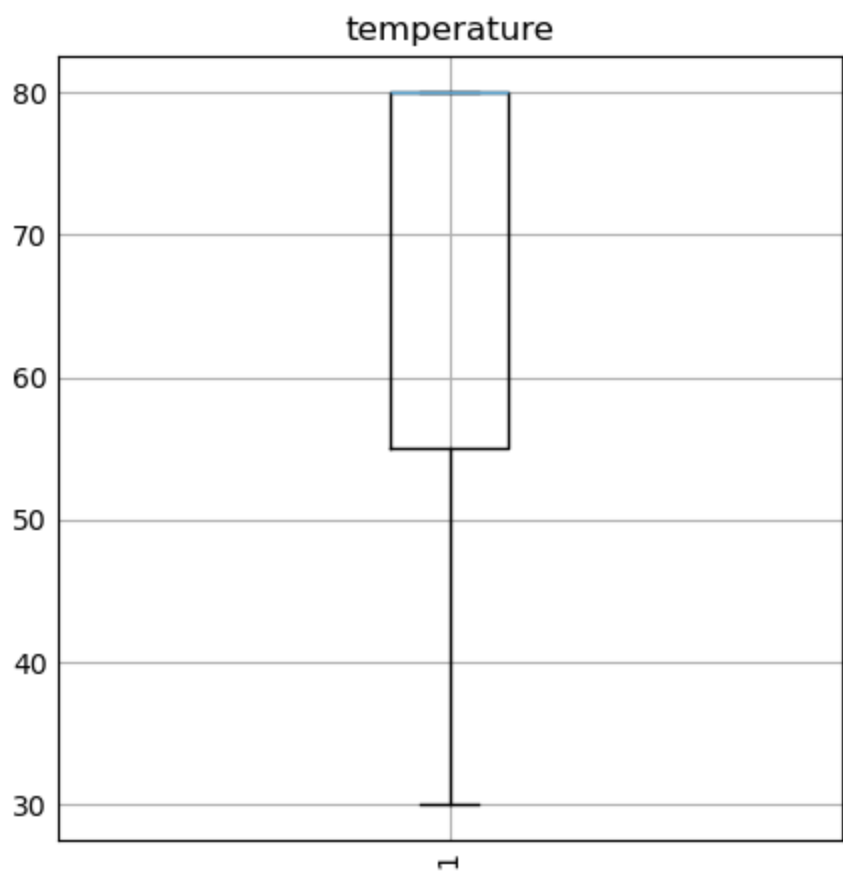
In []:

B] Numerical EDA

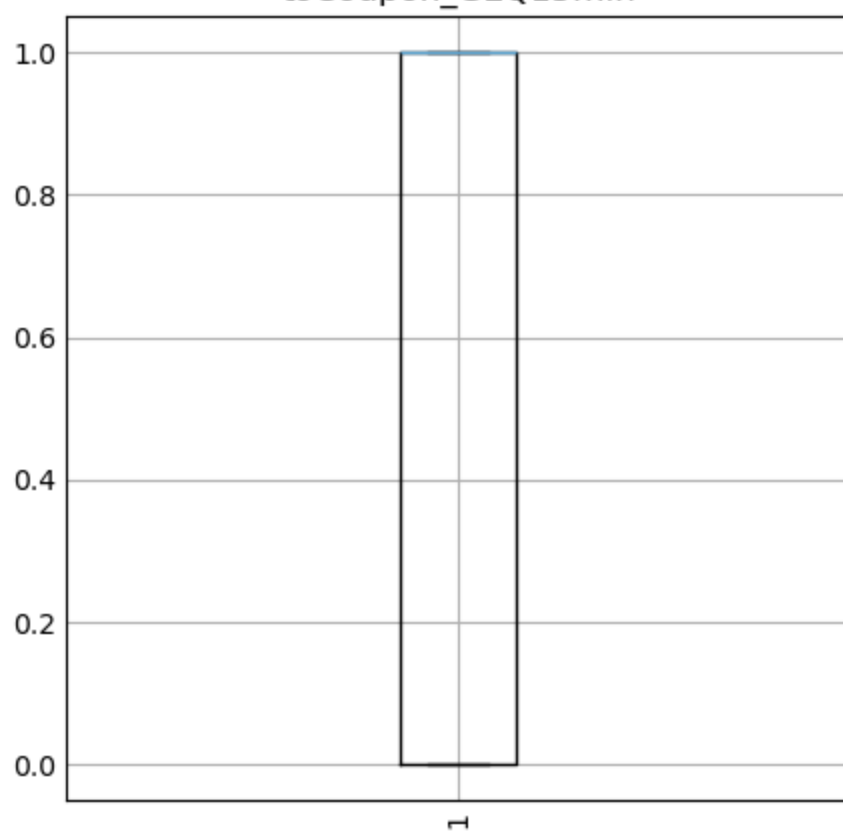
Box Plot

```
In [66]: # whole numerical col. visulizing in boxplot
for i in numerical:
    # if df[i].nunique()<1000:

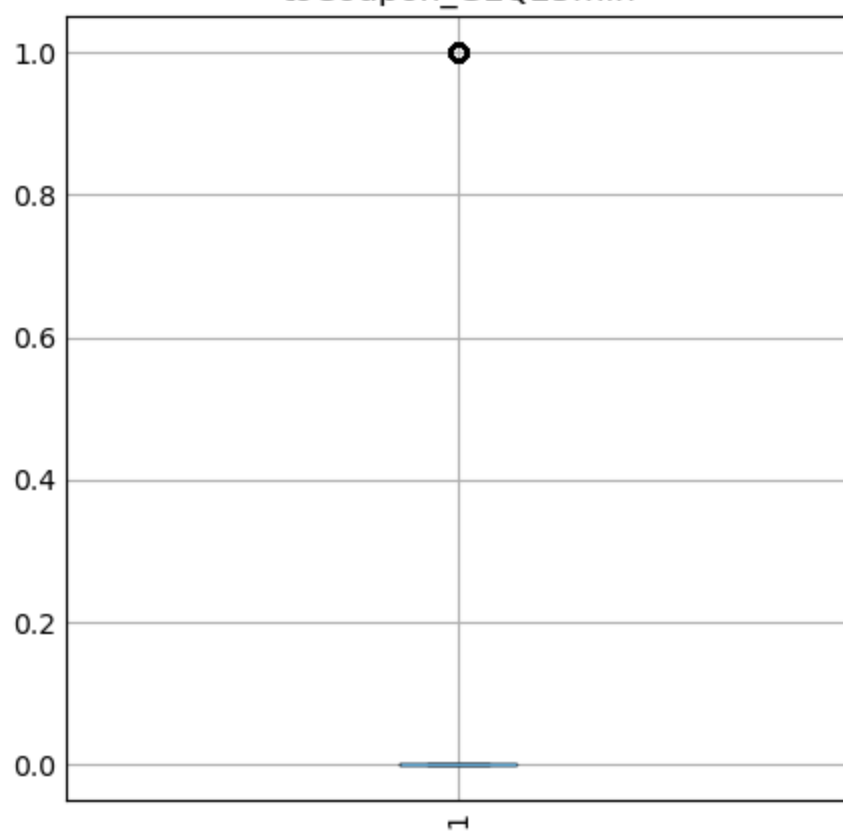
    plt.figure(figsize=(4,4))
    plt.title(i)
    plt.boxplot(x=i, data=df)
    plt.xticks(rotation=90)
plt.show()
```

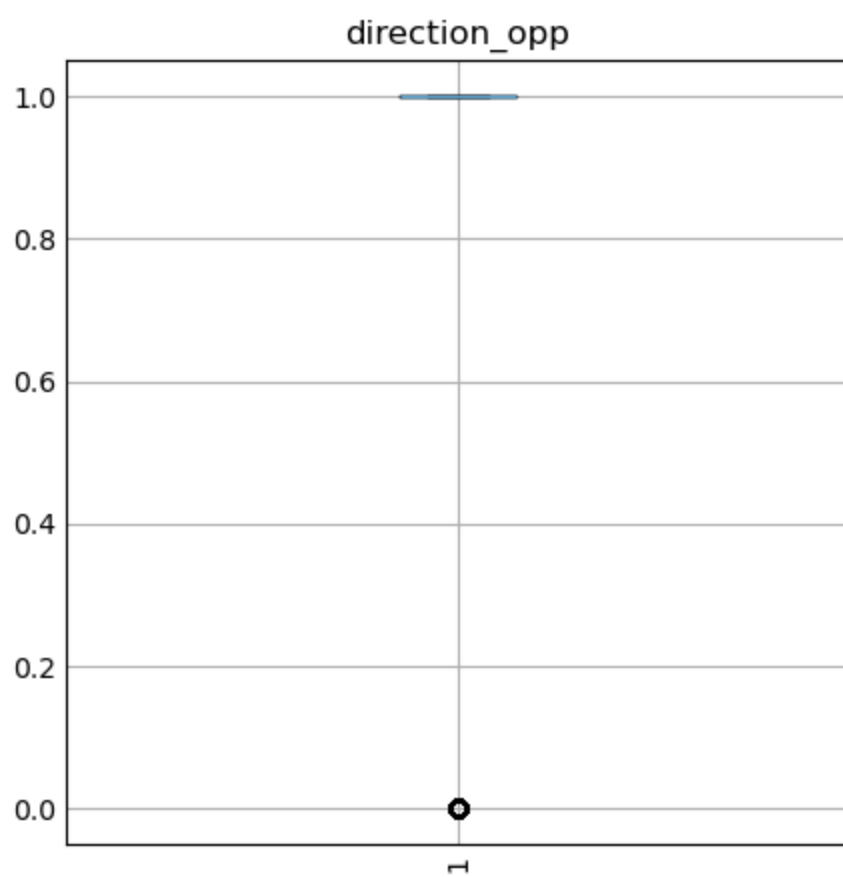
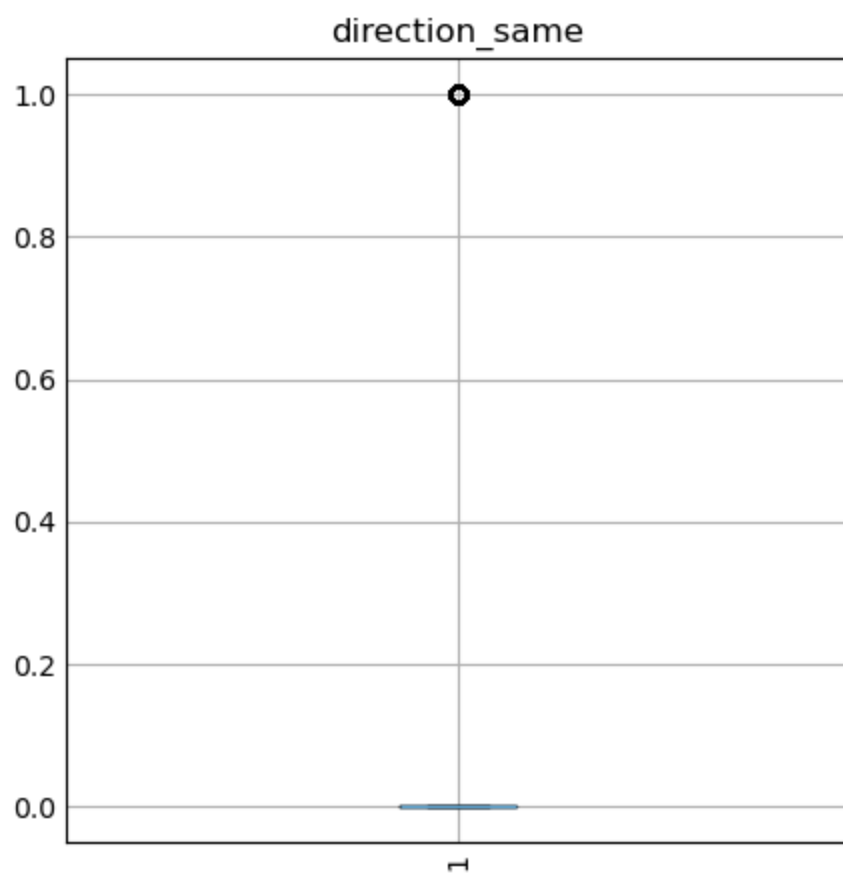


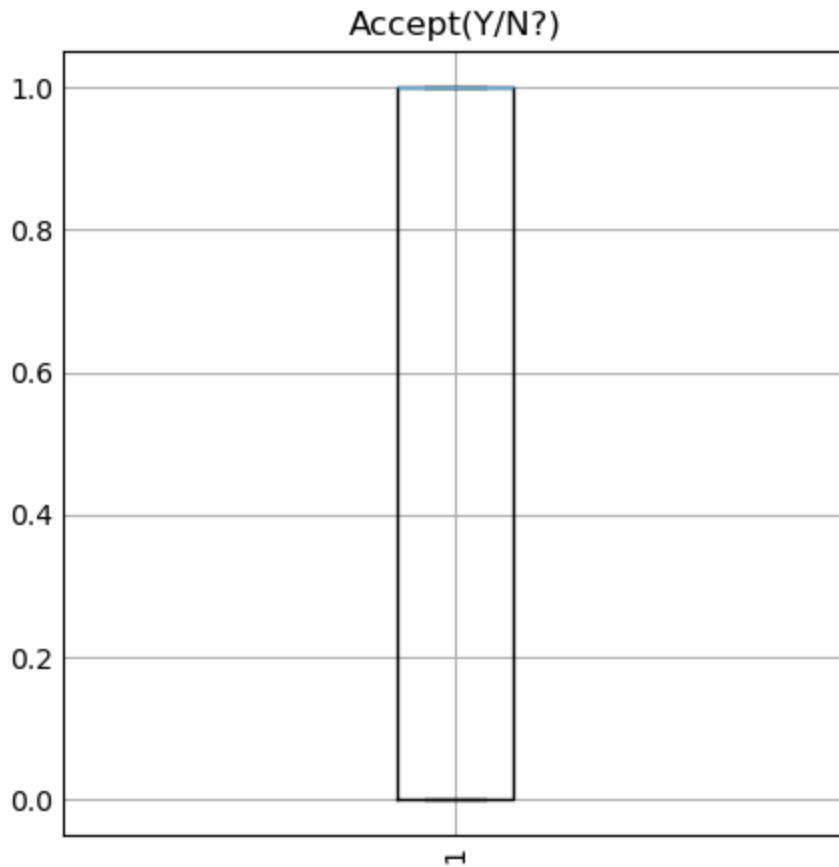
toCoupon_GEQ15min



toCoupon_GEQ25min







There are none outliers in Boxplot

```
In [45]: df[numerical].describe()
```

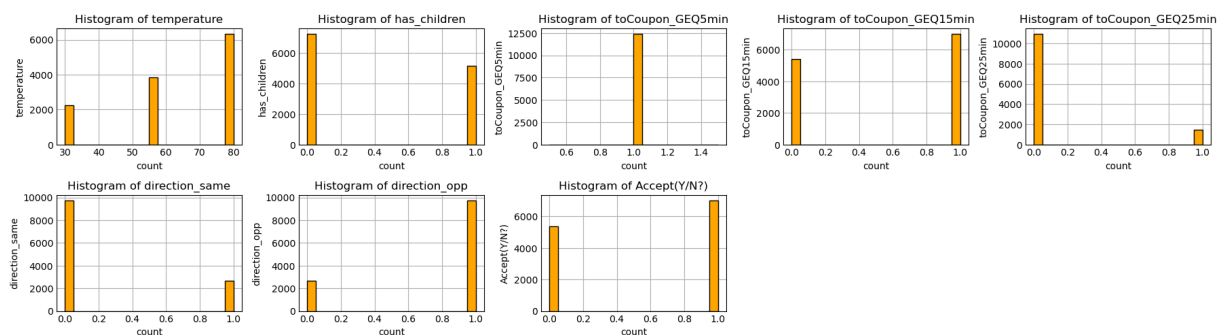
```
Out[45]:
```

	temperature	has_children	toCoupon_GEQ5min	toCoupon_GEQ15min
count	12393.000000	12393.000000	12393.0	12393.000000
mean	63.252643	0.415557	1.0	0.563625
std	19.075396	0.492838	0.0	0.495955
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

Histogram

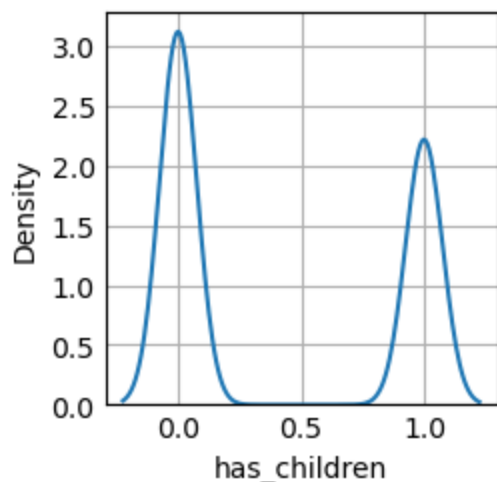
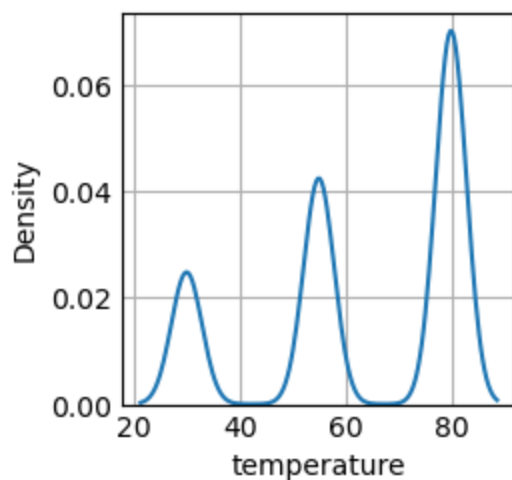
```
In [46]: plt.figure(figsize=(18, 12))
for idx, i in enumerate(numerical):
    plt.subplot(5, 5, idx + 1) # Adjust grid size (5x5) based on number of
    plt.hist(df[i], bins=20, color='orange', edgecolor='black')
    plt.title(f'Histogram of {i}')
```

```
plt.xlabel('count')
plt.ylabel(i)
plt.tight_layout()
plt.show()
```

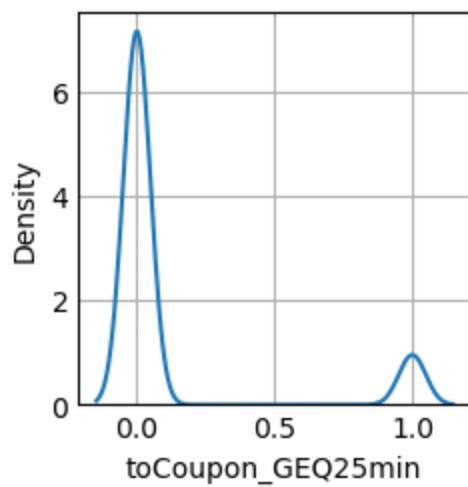
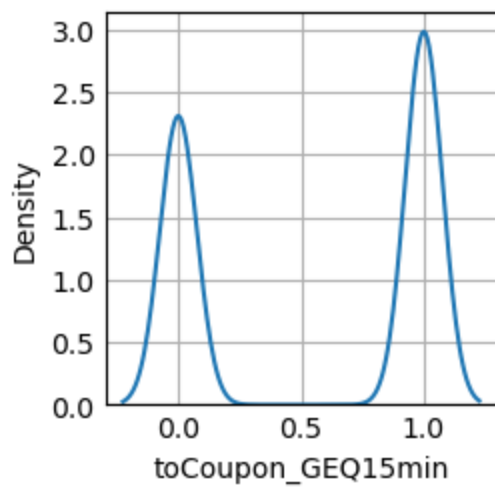
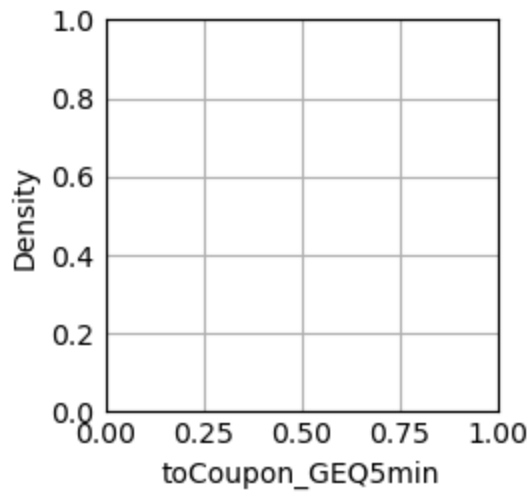


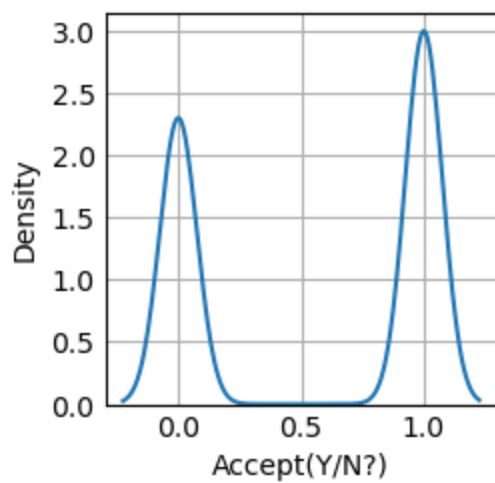
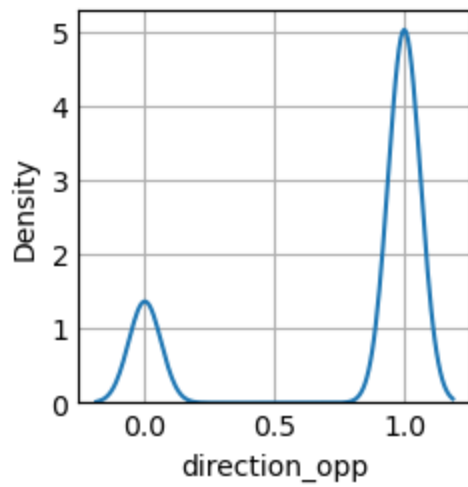
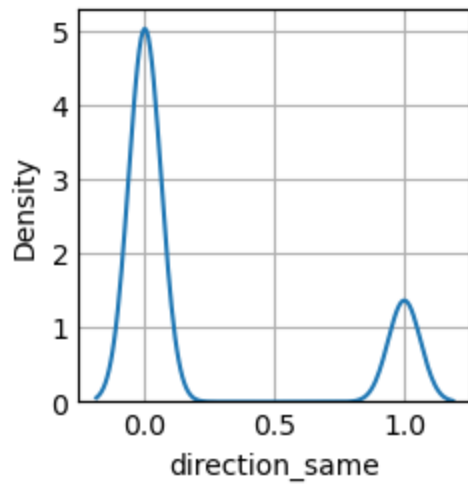
KDE Plot

```
In [47]: for i in numerical:
          if df[i].nunique() < 1000:
              sns.kdeplot(data=df[i])
          plt.show()
```



```
C:\Users\Welcome\AppData\Local\Temp\ipykernel_12880\2305473507.py:3: UserWarning: Dataset has 0 variance; skipping density estimate. Pass `warn_singular=False` to disable this warning.  
sns.kdeplot(data=df[i])
```





Correlation matrix of numerical column

```
In [48]: df[numerical].corr()
```

```
Out[48]:
```

	temperature	has_children	toCoupon_GEQ5min	toCoupe
temperature	1.000000	-0.016963		NaN
has_children	-0.016963	1.000000		NaN
toCoupon_GEQ5min	NaN	NaN		NaN
toCoupon_GEQ15min	-0.141124	0.078686		NaN
toCoupon_GEQ25min	-0.230067	-0.011651		NaN
direction_same	0.088885	-0.032276		NaN
direction_opp	-0.088885	0.032276		NaN
Accept(Y/N?)	0.064074	-0.044889		NaN

```
In [49]: df['toCoupon_GEQ5min'].isnull().sum()
```

```
Out[49]: 0
```

```
In [50]: df['toCoupon_GEQ5min'].dtype
```

```
Out[50]: dtype('int64')
```

```
In [51]: df['toCoupon_GEQ5min'].nunique()
```

```
Out[51]: 1
```

```
In [52]: df[numerical].nunique()
```

```
Out[52]: temperature      3
has_children      2
toCoupon_GEQ5min    1
toCoupon_GEQ15min    2
toCoupon_GEQ25min    2
direction_same      2
direction_opp      2
Accept(Y/N?)      2
dtype: int64
```

Dropping 'toCoupon_GEQ5min' because there is nan values in column

```
In [53]: df.drop(columns=['toCoupon_GEQ5min'], axis=1, inplace=True)
```

```
In [59]: print(df.columns) ## checking the column is it drop or not..
```

```
Index(['destination', 'passanger', 'weather', 'temperature', 'coupon',
      'expiration', 'gender', 'age', 'maritalStatus', 'has_children',
      'education', 'occupation', 'income', 'Bar', 'CoffeeHouse', 'CarryAway',
      'RestaurantLessThan20', 'Restaurant20To50', 'toCoupon_GEQ15min',
      'toCoupon_GEQ25min', 'direction_same', 'direction_opp', 'Accept(Y/N?)'],
      dtype='object')
```

```
In [60]: numerical = [col for col in df.select_dtypes(include=['int64', 'float64']).columns
print(numerical) # Ensure 'toCoupon_GEQ5min' is not in this list

['temperature', 'has_children', 'toCoupon_GEQ15min', 'toCoupon_GEQ25min', 'direction_same', 'direction_opp', 'Accept(Y/N?)']
```

```
In [61]: df[numerical].corr()
```

```
Out[61]:
```

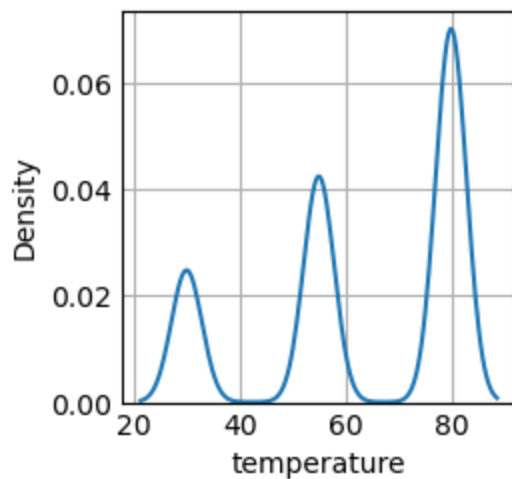
	temperature	has_children	toCoupon_GEQ15min	toCoupon_GEQ25min
temperature	1.000000	-0.016963	-0.141124	-0.230067
has_children	-0.016963	1.000000	0.078686	-0.011651
toCoupon_GEQ15min	-0.141124	0.078686	1.000000	0.321919
toCoupon_GEQ25min	-0.230067	-0.011651	0.321919	1.000000
direction_same	0.088885	-0.032276	-0.297284	0.032276
direction_opp	-0.088885	0.032276	0.297284	-0.032276
Accept(Y/N?)	0.064074	-0.044889	-0.086050	0.064074

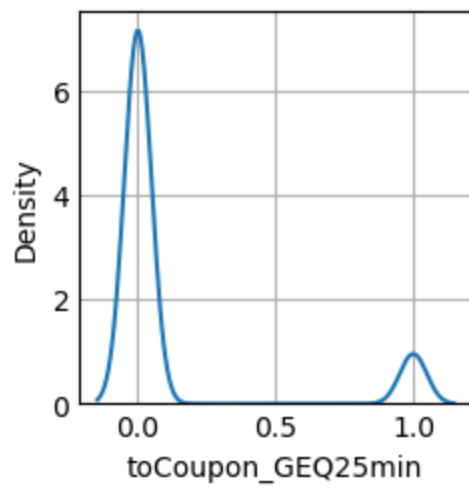
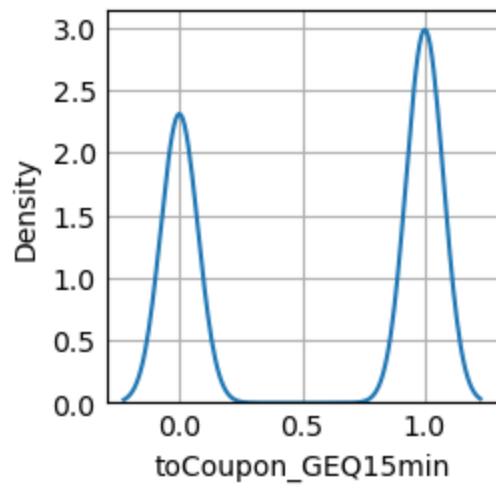
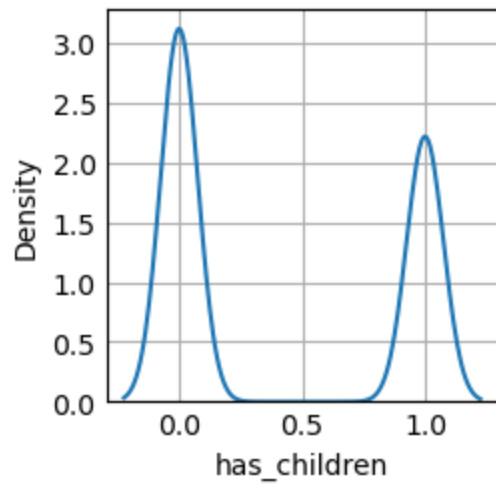
```
In [62]: df.isnull().sum() # Checking Null values again
```

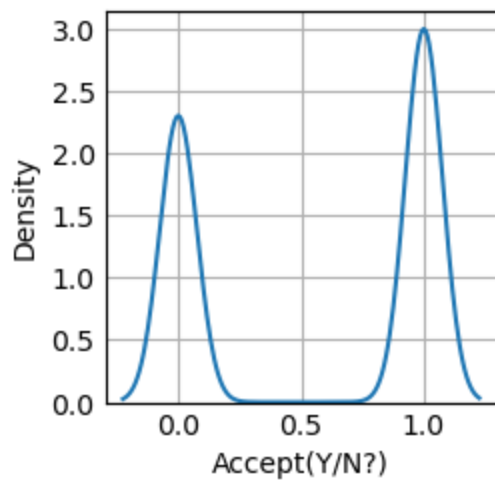
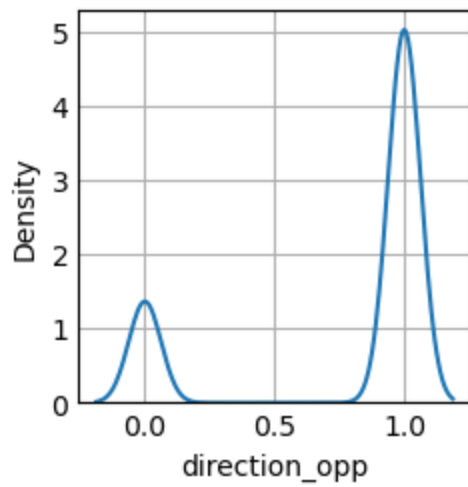
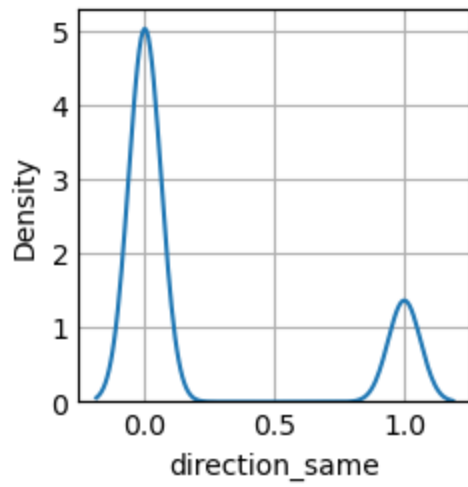
```
Out[62]: destination      0
passanger                0
weather                  0
temperature              0
coupon                   0
expiration               0
gender                   0
age                      0
maritalStatus            0
has_children             0
education                0
occupation               0
income                   0
Bar                      0
CoffeeHouse              0
CarryAway                0
RestaurantLessThan20     0
Restaurant20To50         0
toCoupon_GEQ15min        0
toCoupon_GEQ25min        0
direction_same           0
direction_opp            0
Accept(Y/N?)             0
dtype: int64
```

KDE plot after removing nan values col.

```
In [63]: for i in numerical:
          if df[i].nunique():
              sns.kdeplot(data=df[i])
              plt.show()
```

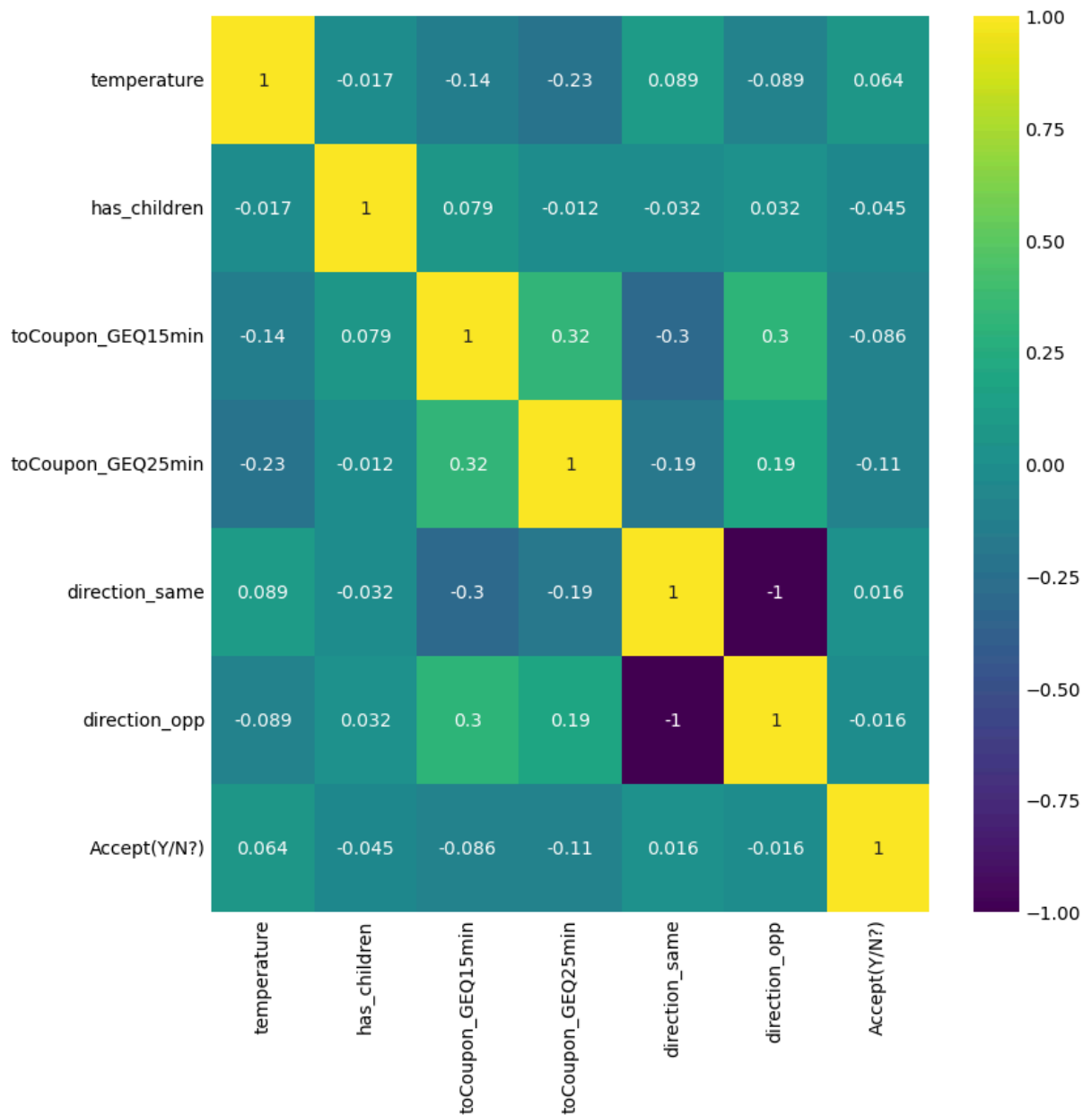






Heatmap

```
In [64]: plt.figure(figsize=(7,7))
sns.heatmap(data=df[numerical].corr(),cmap='viridis',vmin=-1,vmax=1,annot=True)
plt.show()
```



6 Lable encoding

```
In [73]: from sklearn.preprocessing import LabelEncoder
```

```
In [75]: le=LabelEncoder()
```

```
In [78]: df2=pd.DataFrame()
for i in df.columns:
    df2[i]=le.fit_transform(df[i])
df2
```

```
Out[78]:
```

	destination	passanger	weather	temperature	coupon	expiration	ge
0	1	0	2	1	4	0	
1	1	1	2	2	2	1	
2	1	1	2	2	1	1	
3	1	1	2	2	2	1	
4	1	1	2	2	2	0	
...
12388	0	3	0	1	1	0	
12389	2	0	0	1	1	0	
12390	2	0	1	0	2	0	
12391	2	0	1	0	0	0	
12392	2	0	2	2	3	1	

12393 rows × 23 columns

7 X&Y Train Test split

```
In [79]: x=df2.drop(columns=['Accept(Y/N?)'],axis=1)
y=df2['Accept(Y/N?)']
```

```
In [80]: x.head()
```

```
Out[80]:
```

	destination	passanger	weather	temperature	coupon	expiration	gender
0	1	0	2	1	4	0	0
1	1	1	2	2	2	1	0
2	1	1	2	2	1	1	0
3	1	1	2	2	2	1	0
4	1	1	2	2	2	0	0

5 rows × 22 columns

```
In [81]: y.head()
```

```
Out[81]: 0    1
1    0
2    1
3    0
4    0
Name: Accept(Y/N?), dtype: int64
```

```
In [82]: x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=42,test_size=0.2)
```

```
In [83]: x_train.head()
```

```
Out[83]:
```

	destination	passanger	weather	temperature	coupon	expiration	ge
3288	2	0	2	2	3	0	
10934	0	0	1	0	2	1	
9835	2	0	0	1	1	1	
7660	2	0	0	1	3	0	
1691	1	2	2	2	1	1	

5 rows × 22 columns

```
In [84]: x_test.head()
```

```
Out[84]:
```

	destination	passanger	weather	temperature	coupon	expiration	ge
10146	1	0	0	1	2	0	
9834	2	0	2	0	0	0	
6902	0	0	2	0	1	1	
2145	1	1	2	2	4	1	
2344	0	0	2	1	3	0	

5 rows × 22 columns

```
In [85]: y_train.head()
```

```
Out[85]:
```

3288	0
10934	0
9835	1
7660	1
1691	1

Name: Accept(Y/N?), dtype: int64

```
In [86]: y_test.head()
```

```
Out[86]:
```

10146	1
9834	1
6902	1
2145	1
2344	1

Name: Accept(Y/N?), dtype: int64

8 Model Building

Logistic Regression

```
In [88]: lr=LogisticRegression()
```

```
In [89]: lr.fit(x_train,y_train)
y_train_predict_lr=lr.predict(x_train)
y_test_predict_lr=lr.predict(x_test)
```

```
In [90]: print("train")
print(f"accuracy_score{accuracy_score(y_train,y_train_predict_lr)},precision_score{precision_score(y_train,y_train_predict_lr)},recall_score{recall_score(y_train,y_train_predict_lr)}")

train
accuracy_score0.6301190236029857,precision_score0.6461538461538462,recall_score0.7740563530037214
```

```
In [92]: print("test")
print(f"accuracy_score{accuracy_score(y_test,y_test_predict_lr)},precision_score{precision_score(y_test,y_test_predict_lr)},recall_score{recall_score(y_test,y_test_predict_lr)}")

test
accuracy_score0.6232351754739814,precision_score0.6275659824046921,recall_score0.7815924032140248
```

Decision Tree

```
In [93]: DTC =DecisionTreeClassifier(max_depth=2,criterion='entropy')
DTC.fit(x_train,y_train)

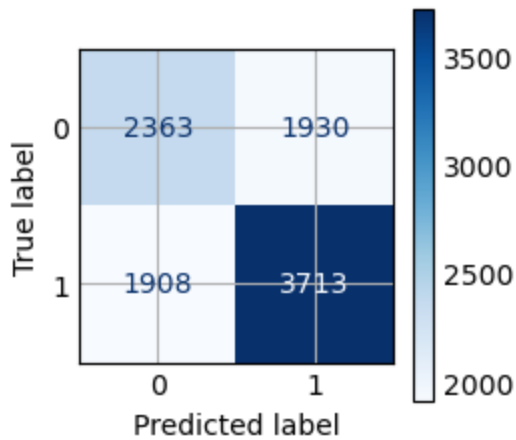
y_pred_train = DTC.predict(x_train)
cm = confusion_matrix(y_pred_train,y_train )

disp = ConfusionMatrixDisplay(confusion_matrix=cm)

print("recall acc for train : " , recall_score(y_pred_train,y_train))
print("precision for train : " ,precision_score(y_pred_train,y_train))
print("f1_score for train : " ,f1_score(y_pred_train,y_train))
print("accuracy : " ,accuracy_score(y_pred_train,y_train))
disp.plot(cmap='Blues')

plt.show()
```

```
recall acc for train :  0.6605586194627291
precision for train :  0.6579833421938686
f1_score for train :  0.6592684659090909
accuracy :  0.6128706879160782
```



```
In [94]: y_pred_test = DTC.predict(x_test)
cm = confusion_matrix(y_pred_test,y_test )

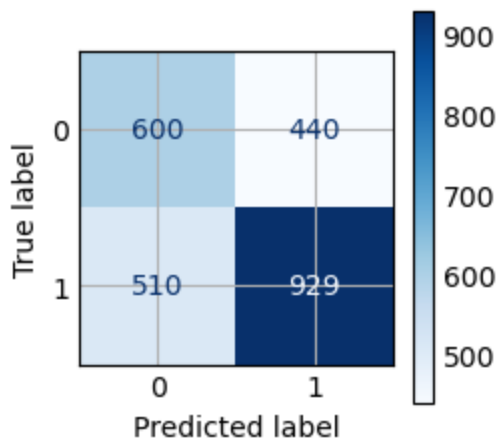
disp = ConfusionMatrixDisplay(confusion_matrix=cm)

print("recall acc for test : " , recall_score(y_pred_test,y_test))
print("precision for test : " , precision_score(y_pred_test,y_test))
print("f1_score for test : " , f1_score(y_pred_test,y_test))
print("accuracy : " ,accuracy_score(y_pred_test,y_test))

disp.plot(cmap='Blues')

plt.show()
```

```
recall acc for test : 0.645587213342599
precision for test : 0.6785975164353543
f1_score for test : 0.6616809116809116
accuracy : 0.6167809600645422
```



Random Forest Clasifier

```
In [112]: for i in range(5,105,5):
rfc=RandomForestClassifier(n_estimators=i,criterion = 'entropy',max_dept
rfc.fit(x_train,y_train)
y_train_predict=rfc.predict(x_train)
y_test_predict=rfc.predict(x_test)
```

```
print("n_estimator =", i)
print("train")
print(f"accuracy_score={accuracy_score(y_train, y_train_predict)}, precision={precision_score(y_train, y_train_predict)}")
print("test")
print(f"accuracy_score={accuracy_score(y_test, y_test_predict)}, precision={precision_score(y_test, y_test_predict)}")
print("")
```



```
n_estimator = 5
train
accuracy_score=0.739560217873714,precision_score=0.7251728703839929,recall_s
core=0.873471557682084
test
accuracy_score=0.672045179507866,precision_score=0.6581342434584755,recall_s
core=0.8451424397370343
```

```
n_estimator = 10
train
accuracy_score=0.7479322170667743,precision_score=0.7252148997134671,recall_
score=0.8970405812511075
test
accuracy_score=0.6926179911254539,precision_score=0.670601461495222,recall_s
core=0.8714390065741418
```

```
n_estimator = 15
train
accuracy_score=0.7489408916683478,precision_score=0.7252857142857143,recall_
score=0.899698741804005
test
accuracy_score=0.6942315449778136,precision_score=0.6701949860724234,recall_
score=0.8787436084733382
```

```
n_estimator = 20
train
accuracy_score=0.751866048012911,precision_score=0.7276498355027893,recall_s
core=0.9014708488392699
test
accuracy_score=0.7006857603872529,precision_score=0.6778218944980148,recall_
score=0.872899926953981
```

```
n_estimator = 25
train
accuracy_score=0.7563042162598346,precision_score=0.7315917898665135,recall_
score=0.9032429558745348
test
accuracy_score=0.7027027027027027,precision_score=0.6801596351197263,recall_
score=0.8714390065741418
```

```
n_estimator = 30
train
accuracy_score=0.7568085535606214,precision_score=0.7320505456634119,recall_
score=0.9034201665780613
test
accuracy_score=0.6990722065348931,precision_score=0.6768881317433276,recall_
score=0.870708546384222
```

```
n_estimator = 35
train
accuracy_score=0.758119830542667,precision_score=0.7333525097080397,recall_s
core=0.9035973772815878
test
accuracy_score=0.7014925373134329,precision_score=0.6781869688385269,recall_
score=0.8743608473338204
```

```
n_estimator = 40
train
accuracy_score=0.7616501916481743,precision_score=0.7356999137683242,recall_
score=0.9071415913521177
test
accuracy_score=0.7039128680919726,precision_score=0.6805002842524162,recall_
score=0.8743608473338204
```

```
n_estimator = 45
train
accuracy_score=0.7615493241880169,precision_score=0.7364095169430426,recall_
score=0.9050150629097997
test
accuracy_score=0.7035094796288827,precision_score=0.6790960451977401,recall_
score=0.8780131482834186
```

```
n_estimator = 50
train
accuracy_score=0.7610449868872302,precision_score=0.7350660539919587,recall_
score=0.9071415913521177
test
accuracy_score=0.7022993142396128,precision_score=0.6781479390175043,recall_
score=0.8772826880934989
```

```
n_estimator = 55
train
accuracy_score=0.7631632035505346,precision_score=0.7369480799654825,recall_
score=0.9080276448697502
test
accuracy_score=0.7022993142396128,precision_score=0.6785512167515563,recall_
score=0.8758217677136596
```

```
n_estimator = 60
train
accuracy_score=0.7631632035505346,precision_score=0.7374261420954028,recall_
score=0.9067871699450647
test
accuracy_score=0.7067365873336022,precision_score=0.6821793416572077,recall_
score=0.8780131482834186
```

```
n_estimator = 65
train
accuracy_score=0.763566673391164,precision_score=0.736826992103374,recall_sc
ore=0.9094453304979621
test
accuracy_score=0.7063331988705123,precision_score=0.6809712027103332,recall_
score=0.8809349890430972
```

```
n_estimator = 70
train
accuracy_score=0.7645753479927375,precision_score=0.7387790445951797,recall_
score=0.9071415913521177
test
accuracy_score=0.709156918112142,precision_score=0.6840909090909091,recall_s
core=0.8794740686632578
```

```

n_estimator = 75
train
accuracy_score=0.7645753479927375,precision_score=0.7385036759406083,recall_
score=0.9078504341662237
test
accuracy_score=0.7075433642597821,precision_score=0.6829545454545455,recall_
score=0.8780131482834186

```

```

n_estimator = 80
train
accuracy_score=0.7638692757716361,precision_score=0.7373490511788384,recall_
score=0.9089136983873826
test
accuracy_score=0.7043162565550625,precision_score=0.6796610169491526,recall_
score=0.8787436084733382

```

```

n_estimator = 85
train
accuracy_score=0.7657857575146257,precision_score=0.7395758187851681,recall_
score=0.9083820662768031
test
accuracy_score=0.7031060911657927,precision_score=0.67871259175607,recall_sc
ore=0.8780131482834186

```

```

n_estimator = 90
train
accuracy_score=0.7656848900544684,precision_score=0.7393310265282583,recall_
score=0.9087364876838561
test
accuracy_score=0.7043162565550625,precision_score=0.6794582392776524,recall_
score=0.8794740686632578

```

```

n_estimator = 95
train
accuracy_score=0.765281420213839,precision_score=0.7389737676563851,recall_s
core=0.9085592769803296
test
accuracy_score=0.7059298104074223,precision_score=0.6799775028121485,recall_
score=0.8831263696128561

```

```

n_estimator = 100
train
accuracy_score=0.7665926971958846,precision_score=0.7402222542935488,recall_
score=0.9089136983873826
test
accuracy_score=0.7043162565550625,precision_score=0.6786516853932584,recall_
score=0.8823959094229364

```

```

In [113]: for i in range(5,105,5):
            rfc=RandomForestClassifier(n_estimators=i,criterion = 'gini',max_depth=7
            rfc.fit(x_train,y_train)
            y_train_predict=rfc.predict(x_train)
            y_test_predict=rfc.predict(x_test)
            print("n_estimator =",i)
            print("train")

```

```
print(f"accuracy_score={accuracy_score(y_train,y_train_predict)},precision={accuracy_score(y_train,y_train_predict)}")
print("test")
print(f"accuracy_score={accuracy_score(y_test,y_test_predict)},precision={accuracy_score(y_test,y_test_predict)}")
print("")
```

```
n_estimator = 5
train
accuracy_score=0.711014726649183,precision_score=0.700201787258576,recall_score=0.860889597731703
test
accuracy_score=0.6692214602662364,precision_score=0.6583958453548759,recall_score=0.83345507669832
```

```
n_estimator = 10
train
accuracy_score=0.7218075448860197,precision_score=0.7017764722338788,recall_score=0.8890660995924153
test
accuracy_score=0.6829366680112948,precision_score=0.6627582356225572,recall_score=0.8670562454346238
```

```
n_estimator = 15
train
accuracy_score=0.7241274964696389,precision_score=0.7024505708716235,recall_score=0.8940279992911572
test
accuracy_score=0.6797095603065753,precision_score=0.6584022038567493,recall_score=0.872899926953981
```

```
n_estimator = 20
train
accuracy_score=0.7276578575751462,precision_score=0.706700379266751,recall_score=0.8915470494417863
test
accuracy_score=0.6873739411052844,precision_score=0.6639072847682119,recall_score=0.8787436084733382
```

```
n_estimator = 25
train
accuracy_score=0.7297760742384507,precision_score=0.7072727272727273,recall_score=0.8961545277334751
test
accuracy_score=0.6793061718434853,precision_score=0.6583885209713024,recall_score=0.8714390065741418
```

```
n_estimator = 30
train
accuracy_score=0.7322977607423845,precision_score=0.7094017094017094,recall_score=0.897217791954634
test
accuracy_score=0.6873739411052844,precision_score=0.6640883977900552,recall_score=0.8780131482834186
```

```
n_estimator = 35
train
accuracy_score=0.7300786766189228,precision_score=0.7075696096264167,recall_score=0.8961545277334751
test
accuracy_score=0.6877773295683743,precision_score=0.6642738818332413,recall_score=0.8787436084733382
```

```
n_estimator = 40
train
accuracy_score=0.7317934234415977,precision_score=0.708905068608233,recall_s
core=0.897217791954634
test
accuracy_score=0.691407825736184,precision_score=0.6666666666666666,recall_s
core=0.8823959094229364
```

```
n_estimator = 45
train
accuracy_score=0.7317934234415977,precision_score=0.7093153759820426,recall_
score=0.8959773170299486
test
accuracy_score=0.691407825736184,precision_score=0.667220376522702,recall_sc
ore=0.8802045288531775
```

```
n_estimator = 50
train
accuracy_score=0.729574339318136,precision_score=0.7070170533967012,recall_s
core=0.8963317384370016
test
accuracy_score=0.6897942718838241,precision_score=0.665380374862183,recall_s
core=0.8816654492330168
```

```
n_estimator = 55
train
accuracy_score=0.7306838813798668,precision_score=0.7083975886723679,recall_
score=0.8954456849193692
test
accuracy_score=0.6922146026623639,precision_score=0.6663007683863886,recall_
score=0.8867786705624543
```

```
n_estimator = 60
train
accuracy_score=0.7330038329634859,precision_score=0.7108077680833099,recall_
score=0.8950912635123162
test
accuracy_score=0.6938281565147236,precision_score=0.6686946902654868,recall_
score=0.8831263696128561
```

```
n_estimator = 65
train
accuracy_score=0.7332055678838006,precision_score=0.7107112735451223,recall_
score=0.8959773170299486
test
accuracy_score=0.6938281565147236,precision_score=0.6688815060908084,recall_
score=0.8823959094229364
```

```
n_estimator = 70
train
accuracy_score=0.733306435343958,precision_score=0.7110485573539761,recall_s
core=0.8952684742158427
test
accuracy_score=0.6970552642194433,precision_score=0.6710963455149501,recall_
score=0.885317750182615
```

```
n_estimator = 75
train
accuracy_score=0.735021182166633,precision_score=0.7125740062024246,recall_s
core=0.8958001063264222
test
accuracy_score=0.6982654296087132,precision_score=0.672787979966611,recall_s
core=0.8831263696128561
```

```
n_estimator = 80
train
accuracy_score=0.7361307242283639,precision_score=0.7134395712875476,recall_
score=0.896508949140528
test
accuracy_score=0.6962484872932634,precision_score=0.6709211986681465,recall_
score=0.8831263696128561
```

```
n_estimator = 85
train
accuracy_score=0.7357272543877346,precision_score=0.7135792002260845,recall_
score=0.8949140528087897
test
accuracy_score=0.6974586526825333,precision_score=0.6716583471991125,recall_
score=0.8845872899926954
```

```
n_estimator = 90
train
accuracy_score=0.734415977405689,precision_score=0.7115546809108799,recall_s
core=0.8970405812511075
test
accuracy_score=0.6954417103670835,precision_score=0.6703662597114317,recall_
score=0.8823959094229364
```

```
n_estimator = 95
train
accuracy_score=0.7341133750252169,precision_score=0.711136076393765,recall_s
core=0.8973950026581605
test
accuracy_score=0.6954417103670835,precision_score=0.6711259754738016,recall_
score=0.8794740686632578
```

```
n_estimator = 100
train
accuracy_score=0.7343151099455316,precision_score=0.7113952508079247,recall_
score=0.897217791954634
test
accuracy_score=0.6966518757563533,precision_score=0.6720580033463469,recall_
score=0.8802045288531775
```

Note: rfc=RandomForestClassifier(n_estimators=70,criterion = 'entropy',max_depth=8,random_state=42)

```
In [116... rfc=RandomForestClassifier(n_estimators=70,criterion = 'entropy',max_depth=8
rfc.fit(x_train,y_train)
y_train_predict=rfc.predict(x_train)
```

```
y_test_predict=rfc.predict(x_test)
print("n_estimator =",70)
print("train")
print(f"accuracy_score={accuracy_score(y_train,y_train_predict)},precision_s
print("test")
print(f"accuracy_score={accuracy_score(y_test,y_test_predict)},precision_sco
print("")
```

```
n_estimator = 70
train
accuracy_score=0.7645753479927375,precision_score=0.7387790445951797,recall_
score=0.9071415913521177
test
accuracy_score=0.709156918112142,precision_score=0.6840909090909091,recall_s
core=0.8794740686632578
```

In [118... pip install xgboost

Collecting xgboostNote: you may need to restart the kernel to use updated packages.

Downloading xgboost-2.1.3-py3-none-win_amd64.whl.metadata (2.1 kB)
Requirement already satisfied: numpy in c:\users\welcome\anaconda3\lib\site-packages (from xgboost) (1.26.4)
Requirement already satisfied: scipy in c:\users\welcome\anaconda3\lib\site-packages (from xgboost) (1.11.4)

Downloading xgboost-2.1.3-py3-none-win_amd64.whl (124.9 MB)

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Installing collected packages: xgboost
Successfully installed xgboost-2.1.3

```

```
In [119... from xgboost import XGBClassifier
```

XGBoost Classifier

```
In [120... from xgboost import XGBClassifier
```

```

xgb_model = XGBClassifier(use_label_encoder=False, eval_metric='logloss')
xgb_model.fit(x_train, y_train)
y_train_predict = xgb_model.predict(x_train)
# Predict
y_test_predict = xgb_model.predict(x_test)

# Evaluate
print("train")
print(f"accuracy_score={accuracy_score(y_train,y_train_predict)},precision_score={precision_score(y_train,y_train_predict)}")
print("test")
print(f"accuracy_score={accuracy_score(y_test,y_test_predict)},precision_score={precision_score(y_test,y_test_predict)}")
print("")

```

C:\Users\Welcome\anaconda3\Lib\site-packages\xgboost\core.py:158: UserWarning: [14:07:35] WARNING: C:\buildkite-agent\builds\buildkite-windows-cpu-autoscaling-group-i-0c55ff5f71b100e98-1\xgboost\xgboost-ci-windows\src\learner.cc:740: Parameters: { "use_label_encoder" } are not used.

```
warnings.warn(smsg, UserWarning)
```

train

accuracy_score=0.9129513818842041,precision_score=0.9066008846546444,recall_score=0.9443558390926812

test

accuracy_score=0.745865268253328,precision_score=0.7478202548625084,recall_score=0.8144631117604091

Adaboost

```

In [129... from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score

# Loop over different values of n_estimators
for i in range(10, 260, 10):
    ada_model = AdaBoostClassifier(n_estimators=i, random_state=42)
    ada_model.fit(x_train, y_train)

    # Predictions
    y_train_predict = ada_model.predict(x_train)
    y_test_predict = ada_model.predict(x_test)

    # Evaluation Metrics
    print(f"n_estimators = {i}")

    print("Train:")
    print(f"Accuracy = {accuracy_score(y_train, y_train_predict):.4f}, "
          f"Precision = {precision_score(y_train, y_train_predict):.4f}, "
          f"Recall = {recall_score(y_train, y_train_predict):.4f}")

    print("Test:")
    print(f"Accuracy = {accuracy_score(y_test, y_test_predict):.4f}, "
          f"Precision = {precision_score(y_test, y_test_predict):.4f}, "
          f"Recall = {recall_score(y_test, y_test_predict):.4f}")

```

```
print("-" * 50) # Separator for readability
```

```
n_estimators = 10
Train:
Accuracy = 0.6587, Precision = 0.6767, Recall = 0.7666
Test:
Accuracy = 0.6571, Precision = 0.6615, Recall = 0.7765
-----
n_estimators = 20
Train:
Accuracy = 0.6751, Precision = 0.6927, Recall = 0.7716
Test:
Accuracy = 0.6789, Precision = 0.6810, Recall = 0.7874
-----
n_estimators = 30
Train:
Accuracy = 0.6808, Precision = 0.7013, Recall = 0.7648
Test:
Accuracy = 0.6801, Precision = 0.6858, Recall = 0.7765
-----
n_estimators = 40
Train:
Accuracy = 0.6838, Precision = 0.7025, Recall = 0.7709
Test:
Accuracy = 0.6757, Precision = 0.6817, Recall = 0.7743
-----
n_estimators = 50
Train:
Accuracy = 0.6852, Precision = 0.7042, Recall = 0.7705
Test:
Accuracy = 0.6765, Precision = 0.6812, Recall = 0.7787
-----
n_estimators = 60
Train:
Accuracy = 0.6867, Precision = 0.7064, Recall = 0.7693
Test:
Accuracy = 0.6785, Precision = 0.6838, Recall = 0.7772
-----
n_estimators = 70
Train:
Accuracy = 0.6868, Precision = 0.7061, Recall = 0.7705
Test:
Accuracy = 0.6773, Precision = 0.6837, Recall = 0.7736
-----
n_estimators = 80
Train:
Accuracy = 0.6871, Precision = 0.7062, Recall = 0.7710
Test:
Accuracy = 0.6789, Precision = 0.6842, Recall = 0.7772
-----
n_estimators = 90
Train:
Accuracy = 0.6886, Precision = 0.7075, Recall = 0.7723
Test:
Accuracy = 0.6785, Precision = 0.6829, Recall = 0.7801
-----
n_estimators = 100
Train:
```

```
Accuracy = 0.6891, Precision = 0.7077, Recall = 0.7732
Test:
Accuracy = 0.6801, Precision = 0.6839, Recall = 0.7823
-----
n_estimators = 110
Train:
Accuracy = 0.6882, Precision = 0.7073, Recall = 0.7714
Test:
Accuracy = 0.6805, Precision = 0.6851, Recall = 0.7801
-----
n_estimators = 120
Train:
Accuracy = 0.6906, Precision = 0.7100, Recall = 0.7718
Test:
Accuracy = 0.6813, Precision = 0.6864, Recall = 0.7787
-----
n_estimators = 130
Train:
Accuracy = 0.6908, Precision = 0.7103, Recall = 0.7714
Test:
Accuracy = 0.6801, Precision = 0.6863, Recall = 0.7750
-----
n_estimators = 140
Train:
Accuracy = 0.6904, Precision = 0.7101, Recall = 0.7709
Test:
Accuracy = 0.6801, Precision = 0.6863, Recall = 0.7750
-----
n_estimators = 150
Train:
Accuracy = 0.6905, Precision = 0.7103, Recall = 0.7707
Test:
Accuracy = 0.6813, Precision = 0.6862, Recall = 0.7794
-----
n_estimators = 160
Train:
Accuracy = 0.6907, Precision = 0.7105, Recall = 0.7707
Test:
Accuracy = 0.6850, Precision = 0.6885, Recall = 0.7845
-----
n_estimators = 170
Train:
Accuracy = 0.6907, Precision = 0.7108, Recall = 0.7700
Test:
Accuracy = 0.6813, Precision = 0.6862, Recall = 0.7794
-----
n_estimators = 180
Train:
Accuracy = 0.6899, Precision = 0.7101, Recall = 0.7694
Test:
Accuracy = 0.6825, Precision = 0.6880, Recall = 0.7779
-----
n_estimators = 190
Train:
Accuracy = 0.6896, Precision = 0.7100, Recall = 0.7687
Test:
```

```

Accuracy = 0.6813, Precision = 0.6869, Recall = 0.7772
-----
n_estimators = 200
Train:
Accuracy = 0.6907, Precision = 0.7103, Recall = 0.7712
Test:
Accuracy = 0.6837, Precision = 0.6881, Recall = 0.7816
-----
n_estimators = 210
Train:
Accuracy = 0.6902, Precision = 0.7099, Recall = 0.7709
Test:
Accuracy = 0.6833, Precision = 0.6877, Recall = 0.7816
-----
n_estimators = 220
Train:
Accuracy = 0.6899, Precision = 0.7095, Recall = 0.7709
Test:
Accuracy = 0.6833, Precision = 0.6881, Recall = 0.7801
-----
n_estimators = 230
Train:
Accuracy = 0.6908, Precision = 0.7103, Recall = 0.7714
Test:
Accuracy = 0.6833, Precision = 0.6879, Recall = 0.7809
-----
n_estimators = 240
Train:
Accuracy = 0.6898, Precision = 0.7094, Recall = 0.7709
Test:
Accuracy = 0.6846, Precision = 0.6887, Recall = 0.7823
-----
n_estimators = 250
Train:
Accuracy = 0.6903, Precision = 0.7098, Recall = 0.7714
Test:
Accuracy = 0.6817, Precision = 0.6866, Recall = 0.7794
-----

```

In [132... *#CATAGORICAL BOOSTING*

```

!pip install catboost
install.packages("catboost")
from catboost import CatBoostClassifier
from sklearn.model_selection import GridSearchCV

```

Collecting catboost

Downloading catboost-1.2.7-cp311-cp311-win_amd64.whl.metadata (1.2 kB)

Collecting graphviz (from catboost)

Downloading graphviz-0.20.3-py3-none-any.whl.metadata (12 kB)

Requirement already satisfied: matplotlib in c:\users\welcome\anaconda3\lib\site-packages (from catboost) (3.8.0)

Requirement already satisfied: numpy<2.0,>=1.16.0 in c:\users\welcome\anaconda3\lib\site-packages (from catboost) (1.26.4)

Requirement already satisfied: pandas>=0.24 in c:\users\welcome\anaconda3\lib\site-packages (from catboost) (2.1.4)

Requirement already satisfied: scipy in c:\users\welcome\anaconda3\lib\site-packages (from catboost) (1.11.4)

Requirement already satisfied: plotly in c:\users\welcome\anaconda3\lib\site-packages (from catboost) (5.9.0)

Requirement already satisfied: six in c:\users\welcome\anaconda3\lib\site-packages (from catboost) (1.16.0)

Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\welcome\anaconda3\lib\site-packages (from pandas>=0.24->catboost) (2.8.2)

Requirement already satisfied: pytz>=2020.1 in c:\users\welcome\anaconda3\lib\site-packages (from pandas>=0.24->catboost) (2023.3.post1)

Requirement already satisfied: tzdata>=2022.1 in c:\users\welcome\anaconda3\lib\site-packages (from pandas>=0.24->catboost) (2023.3)

Requirement already satisfied: contourpy>=1.0.1 in c:\users\welcome\anaconda3\lib\site-packages (from matplotlib->catboost) (1.2.0)

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Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\welcome\anaconda3\lib\site-packages (from matplotlib->catboost) (1.4.4)

Requirement already satisfied: packaging>=20.0 in c:\users\welcome\anaconda3\lib\site-packages (from matplotlib->catboost) (23.1)

Requirement already satisfied: pillow>=6.2.0 in c:\users\welcome\anaconda3\lib\site-packages (from matplotlib->catboost) (10.2.0)

Requirement already satisfied: pyparsing>=2.3.1 in c:\users\welcome\anaconda3\lib\site-packages (from matplotlib->catboost) (3.0.9)

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[illegible]

```

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Downloading graphviz-0.20.3-py3-none-any.whl (47 kB)
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0
Installing collected packages: graphviz, catboost
Successfully installed catboost-1.2.7 graphviz-0.20.3

```

```

-----
NameError                                Traceback (most recent call last)
Cell In[132], line 4
      1 #CATAGORICAL BOOSTING
      3 get_ipython().system('pip install catboost')
----> 4 install.packages("catboost")
      5 from catboost import CatBoostClassifier
      6 from sklearn.model_selection import GridSearchCV

NameError: name 'install' is not defined

```

Create a CatBoostClassifier

```

model = CatBoostClassifier(iterations=500, # Number of boosting iterations

depth=6, # Depth of the tree

learning_rate=0.1,

loss_function='MultiClass', # For multiclass classification

verbose=200) # Print progress every 200 iterations

```

CATAGORICAL BOOSTING

```

In [135... # Import Libraries
from catboost import CatBoostClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score, c
import seaborn as sns
import matplotlib.pyplot as plt

# Define the base CatBoost model
cat_model = CatBoostClassifier(
    iterations=50, # Number of boosting iterations
    depth=6,      # Depth of the tree
    learning_rate=0.1,
    loss_function='MultiClass', # For multiclass classification
    verbose=200 # Print progress every 200 iterations
)

# Define hyperparameter grid for GridSearchCV
param_grid = {
    'iterations': [50, 100], # We are taking here the iterations is (50,100
    'depth': [4, 6, 8],
    'learning_rate': [0.01, 0.1, 0.2],

```

```

    'l2_leaf_reg': [1, 3, 5],
}

# Perform Grid Search with Cross Validation
grid_search = GridSearchCV(estimator=cat_model, param_grid=param_grid, cv=5,
grid_search.fit(x_train, y_train) # Fit the model

# Get the best parameters
best_params = grid_search.best_params_
print("Best Parameters:", best_params)

# Train the best model
best_model = grid_search.best_estimator_

# Model Evaluation
train_pred = best_model.predict(x_train)
test_pred = best_model.predict(x_test)

print("\n--- Train Performance ---")
print(f"Accuracy: {accuracy_score(y_train, train_pred):.4f}")
print(f"Precision: {precision_score(y_train, train_pred, average='weighted')}")
print(f"Recall: {recall_score(y_train, train_pred, average='weighted'):.4f}")

print("\n--- Test Performance ---")
print(f"Accuracy: {accuracy_score(y_test, test_pred):.4f}")
print(f"Precision: {precision_score(y_test, test_pred, average='weighted')}")
print(f"Recall: {recall_score(y_test, test_pred, average='weighted'):.4f}")

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, test_pred)

# Plot Confusion Matrix
plt.figure(figsize=(6, 5))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Pastel1',
            xticklabels=best_model.classes_, yticklabels=best_model.classes_)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()

# Classification Report
print("\nClassification Report:\n", classification_report(y_test, test_pred))

```

0: learn: 0.6589250 total: 77.8ms remaining: 7.71s
99: learn: 0.3665393 total: 1.52s remaining: 0us
Best Parameters: {'depth': 8, 'iterations': 100, 'l2_leaf_reg': 3, 'learning_rate': 0.2}

--- Train Performance ---

Accuracy: 0.8652

Precision: 0.8667

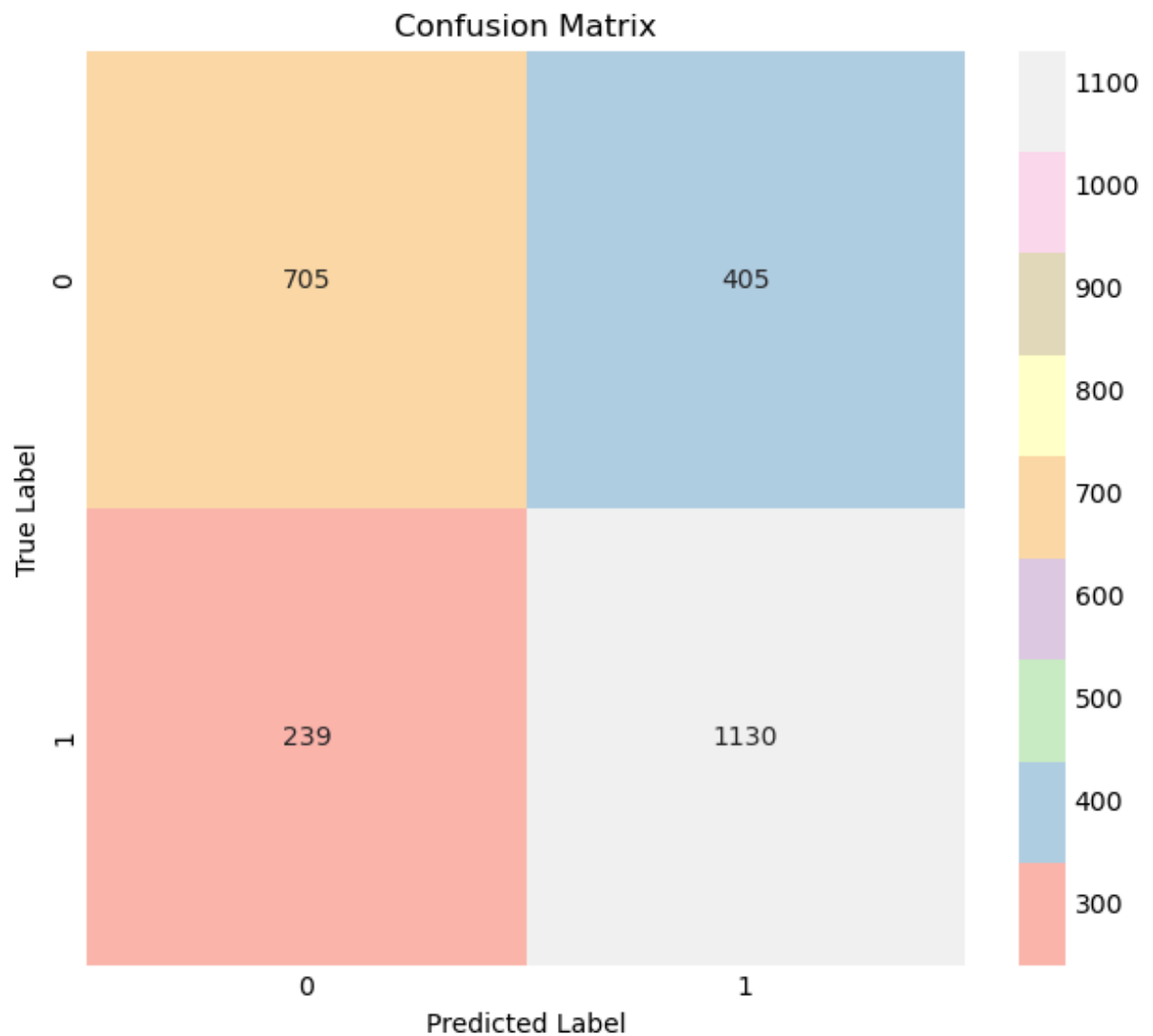
Recall: 0.8652

--- Test Performance ---

Accuracy: 0.7402

Precision: 0.7409

Recall: 0.7402



Classification Report:					
	precision	recall	f1-score	support	
0	0.75	0.64	0.69	1110	
1	0.74	0.83	0.78	1369	
accuracy			0.74	2479	
macro avg	0.74	0.73	0.73	2479	
weighted avg	0.74	0.74	0.74	2479	

```
In [136... # Import Libraries
from catboost import CatBoostClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score, c
import seaborn as sns
import matplotlib.pyplot as plt

# Define the base CatBoost model
cat_model = CatBoostClassifier(
    iterations=500, # Number of boosting iterations
    depth=6, # Depth of the tree
    learning_rate=0.1,
    loss_function='MultiClass', # For multiclass classification
    verbose=200 # Print progress every 200 iterations
)

# Define hyperparameter grid for GridSearchCV
param_grid = {
    'iterations': [500, 1000], #Now we are taking iterations (500,1000) and
    'depth': [4, 6, 8],
    'learning_rate': [0.01, 0.1, 0.2],
    'l2_leaf_reg': [1, 3, 5],
}

# Perform Grid Search with Cross Validation
grid_search = GridSearchCV(estimator=cat_model, param_grid=param_grid, cv=5,
grid_search.fit(x_train, y_train) # Fit the model

# Get the best parameters
best_params = grid_search.best_params_
print("Best Parameters:", best_params)

# Train the best model
best_model = grid_search.best_estimator_

# Model Evaluation
train_pred = best_model.predict(x_train)
test_pred = best_model.predict(x_test)

print("\n--- Train Performance ---")
print(f"Accuracy: {accuracy_score(y_train, train_pred):.4f}")
print(f"Precision: {precision_score(y_train, train_pred, average='weighted')}")
print(f"Recall: {recall_score(y_train, train_pred, average='weighted'):.4f}")

print("\n--- Test Performance ---")
```

```

print(f"Accuracy: {accuracy_score(y_test, test_pred):.4f}")
print(f"Precision: {precision_score(y_test, test_pred, average='weighted'):.4f}")
print(f"Recall: {recall_score(y_test, test_pred, average='weighted'):.4f}")

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, test_pred)

# Plot Confusion Matrix
plt.figure(figsize=(6, 5))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Pastel1',
            xticklabels=best_model.classes_, yticklabels=best_model.classes_)
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()

# Classification Report
print("\nClassification Report:\n", classification_report(y_test, test_pred))

```

```

0:      learn: 0.6781240      total: 16.9ms   remaining: 8.43s
200:    learn: 0.4670769      total: 1.3s    remaining: 1.94s
400:    learn: 0.4041547      total: 2.5s    remaining: 617ms
499:    learn: 0.3827739      total: 3.1s    remaining: 0us
Best Parameters: {'depth': 6, 'iterations': 500, 'l2_leaf_reg': 5, 'learning
_rate': 0.1}

```

--- Train Performance ---

```

Accuracy: 0.8466
Precision: 0.8477
Recall: 0.8466

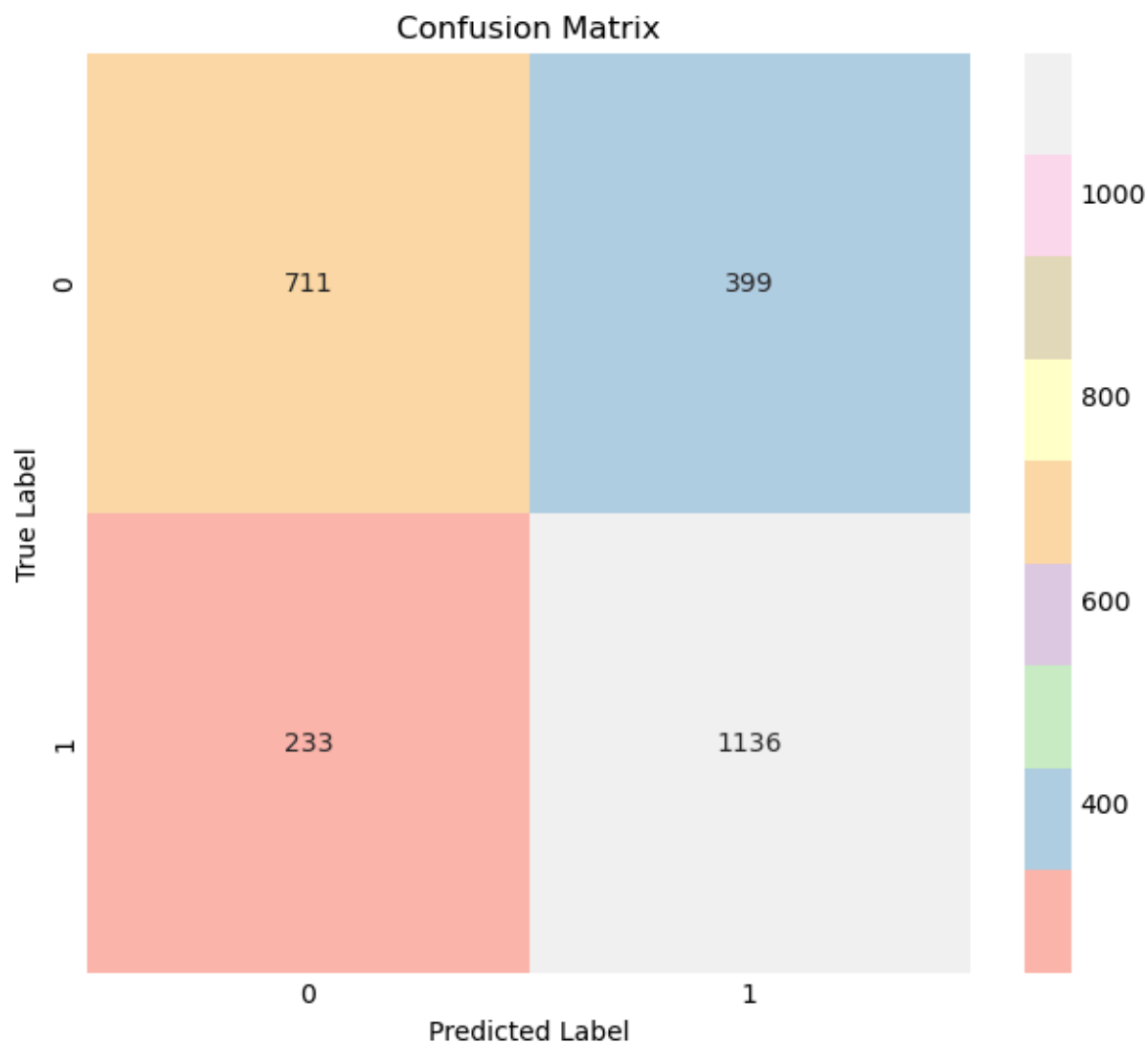
```

--- Test Performance ---

```

Accuracy: 0.7451
Precision: 0.7459
Recall: 0.7451

```



Classification Report:

	precision	recall	f1-score	support
0	0.75	0.64	0.69	1110
1	0.74	0.83	0.78	1369
accuracy			0.75	2479
macro avg	0.75	0.74	0.74	2479
weighted avg	0.75	0.75	0.74	2479

Catboost for iterations 500,100 for checking the accuracy

Note: As comapare to iterations[50, 100] & iterations[500, 1000], iterations[50, 100] Gives better accuracy

Note: CATBOOST gives Better accuracy as compared to other models

```
In [ ]:
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In [ ]:
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This notebook was converted with convert.ploomber.io