Will a Customer Accept the Coupon?

Context

Imagine driving through town and a coupon is delivered to your cell phone for a restaraunt near where you are driving. Would you accept that coupon and take a short detour to the restaraunt? Would you accept the coupon but use it on a sunbsequent trip? Would you ignore the coupon entirely? What if the coupon was for a bar instead of a restaraunt? What about a coffee house? Would you accept a bar coupon with a minor passenger in the car? What about if it was just you and your partner in the car? Would weather impact the rate of acceptance? What about the time of day?

Obviously, proximity to the business is a factor on whether the coupon is delivered to the driver or not, but what are the factors that determine whether a driver accepts the coupon once it is delivered to them? How would you determine whether a driver is likely to accept a coupon?

Overview

The goal of this project is to use what you know about visualizations and probability distributions to distinguish between customers who accepted a driving coupon versus those that did not.

Data

This data comes to us from the UCI Machine Learning repository and was collected via a survey on Amazon Mechanical Turk. The survey describes different driving scenarios including the destination, current time, weather, passenger, etc., and then ask the person whether he will accept the coupon if he is the driver. Answers that the user will drive there 'right away' or 'later before the coupon expires' are labeled as 'Y = 1' and answers 'no, I do not want the coupon' are labeled as 'Y = 0'. There are five different types of coupons -- less expensive restaurants (under $20), coffee houses, carry out & take away, bar, and more expensive restaurants (\$20 - $50).

Deliverables

Your final product should be a brief report that highlights the differences between customers who did and did not accept the coupons. To explore the data you will utilize your knowledge of plotting, statistical summaries, and visualization using Python. You will publish your findings in a public facing github repository as your first portfolio piece.

Data Description

The attributes of this data set include:

1. User attributes
   - Gender: male, female
   - Age: below 21, 21 to 25, 26 to 30, etc.
   - Marital Status: single, married partner, unmarried partner, or widowed
   - Number of children: 0, 1, or more than 1
   - Education: high school, bachelors degree, associates degree, or graduate degree
   - Occupation: architecture & engineering, business & financial, etc.
   - Annual income: less than $12500, \$12500 - $24999, \$25000 - $37499, etc.
   - Number of times that he/she goes to a bar: 0, less than 1, 1 to 3, 4 to 8 or greater than 8
   - Number of times that he/she buys takeaway food: 0, less than 1, 1 to 3, 4 to 8 or greater than 8
   - Number of times that he/she goes to a coffee house: 0, less than 1, 1 to 3, 4 to 8 or greater than 8
   - Number of times that he/she eats at a restaurant with average expense less than $20 per person: 0, less than 1, 1 to 3, 4 to 8 or greater than 8

1. Contextual attributes
   - Driving destination: home, work, or no urgent destination
   - Location of user, coupon and destination: we provide a map to show the geographical location of the user, destination, and the venue, and we mark the distance between each two places with time of driving. The user can see whether the venue is in the same direction as the destination.
   - Weather: sunny, rainy, or snowy
   - Temperature: 30F, 55F, or 80F
   - Time: 10AM, 2PM, or 6PM
   - Passenger: alone, partner, kid(s), or friend(s)

1. Coupon attributes
   - time before it expires: 2 hours or one day

In [1]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import plotly.express as px


#Supress Warnings
import warnings
warnings.filterwarnings('ignore')
```

Problems

Use the prompts below to get started with your data analysis.

1. Read in the `coupons.csv` file.

In [2]:
```
data = pd.read_csv('data/coupons.csv')
```

In [3]:
```
#Get a first impression of the data on hand
data.head()
```

Out[3]:

	destination	passanger	weather	temperature	time	coupon	expiration	gender	age	maritalStatus	...	CoffeeHouse	CarryAway	RestaurantLessThan20	Restaurant20To50
0	No Urgent Place	Alone	Sunny	55	2PM	Restaurant(<20)	1d	Female	21	Unmarried partner	...	never	NaN	4~8	1~3
1	No Urgent Place	Friend(s)	Sunny	80	10AM	Coffee House	2h	Female	21	Unmarried partner	...	never	NaN	4~8	1~3
2	No Urgent Place	Friend(s)	Sunny	80	10AM	Carry out & Take away	2h	Female	21	Unmarried partner	...	never	NaN	4~8	1~3
3	No Urgent Place	Friend(s)	Sunny	80	2PM	Coffee House	2h	Female	21	Unmarried partner	...	never	NaN	4~8	1~3
4	No Urgent Place	Friend(s)	Sunny	80	2PM	Coffee House	1d	Female	21	Unmarried partner	...	never	NaN	4~8	1~3

5 rows × 26 columns

2. Investigate the dataset for missing or problematic data.

In [4]:
```
#Explore the DataFrame and the data types available for our analysis
data.info()
```

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

As we can see, the dataset contains 12,684 rows and 26 columns. 8 of the columns are numeric variables indicated by int64. At first sight, we can see the column "car" only has 0.8% of the data as non-null. All null values are important to explore further to get a better understanding of the proper strategy to address such situation.

In [5]:
```
#Explore the integer columns
data.describe()
```

Out[5]:

	temperature	has_children	toCoupon_GEQ5min	toCoupon_GEQ15min	toCoupon_GEQ25min	direction_same	direction_opp	Y
count	12684.000000	12684.000000	12684.0	12684.000000	12684.000000	12684.000000	12684.000000	12684.000000
mean	63.301798	0.414144	1.0	0.561495	0.119126	0.214759	0.785241	0.568433
std	19.154486	0.492593	0.0	0.496224	0.323950	0.410671	0.410671	0.495314
min	30.000000	0.000000	1.0	0.000000	0.000000	0.000000	0.000000	0.000000
25%	55.000000	0.000000	1.0	0.000000	0.000000	0.000000	1.000000	0.000000
50%	80.000000	0.000000	1.0	1.000000	0.000000	0.000000	1.000000	1.000000
75%	80.000000	1.000000	1.0	1.000000	0.000000	0.000000	1.000000	1.000000
max	80.000000	1.000000	1.0	1.000000	1.000000	1.000000	1.000000	1.000000

Exploring the int64 columns, we can see the column 'toCoupon_GEQ5min' is filled with the integer 1. This means that every coupon given was at least 5 min away from the person. Since this column does not provide valuable information, we will drop the column.

Additionally, it is important to note that the integer variables are not continuous.

In [6]:
```
#Explore the null values. Count the number of null/NaN values in each column.
data.isnull().sum()
```

Out[6]:
```
destination                 0
passanger                   0
weather                     0
temperature                 0
time                        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
Y                           0
dtype: int64
```

Clearly, we observe the column "car" is mostly empty. With the majority of the column being null values, we can understand that the statistical value of the data gathered will be minimal in our analysis. Considering the "toCoupon_GE..." columns were gathered. One can assume that the measurement was used for people in vehicles. Hence, we will drop the car column and assume that all observations were in a car.

The 'Bar', 'CoffeeHouse', 'CarryAway', 'RestaurantLessThan20' and 'Restaurant20To50' columns have a similar numbuer of NaN. (roughly 1-2% of the overall dataset). We can drop NaN rows or impute a value to the null values.

3. Decide what to do about your missing data -- drop, replace, other...

In [7]:
```
# As mentioned above we will remove the column 'car' and 'toCoupon_GEQ5min'.
data_drop = data.drop(['car','toCoupon_GEQ5min'], 1)
data_drop.head()
```

Out[7]:

	destination	passanger	weather	temperature	time	coupon	expiration	gender	age	maritalStatus	...	Bar	CoffeeHouse	CarryAway	RestaurantLessThan20	Restauran
0	No Urgent Place	Alone	Sunny	55	2PM	Restaurant(<20)	1d	Female	21	Unmarried partner	...	never	never	NaN	4~8	
1	No Urgent Place	Friend(s)	Sunny	80	10AM	Coffee House	2h	Female	21	Unmarried partner	...	never	never	NaN	4~8	
2	No Urgent Place	Friend(s)	Sunny	80	10AM	Carry out & Take away	2h	Female	21	Unmarried partner	...	never	never	NaN	4~8	
3	No Urgent Place	Friend(s)	Sunny	80	2PM	Coffee House	2h	Female	21	Unmarried partner	...	never	never	NaN	4~8	
4	No Urgent Place	Friend(s)	Sunny	80	2PM	Coffee House	1d	Female	21	Unmarried partner	...	never	never	NaN	4~8	

5 rows × 24 columns

In [8]:
```
#explore the number of observations we lose when we drop NaN
data_clean = data_drop.dropna()
print(data_clean.shape)
```

```
(12079, 24)
```

The data_clean has 24 columns instead of 26 (due to the dropped columns). When dropping all NaN rows, we are left with 12,079 rows instead 12,684. Roughly, we eliminated 5% of the dataset. Considering the resulting size of observations, this action can be acceptable. We will explore the integer column statistics to ensure that the nature of the data did not vary significantly.

In [9]:
```
#Explore the statistical significance of the dropped data
data_clean.describe()
```

Out[9]:

	temperature	has_children	toCoupon_GEQ15min	toCoupon_GEQ25min	direction_same	direction_opp	Y
count	12079.000000	12079.000000	12079.000000	12079.000000	12079.000000	12079.000000	12079.000000
mean	63.334713	0.408478	0.561222	0.119381	0.215167	0.784833	0.569335
std	19.133246	0.491573	0.496258	0.324249	0.410955	0.410955	0.495190
min	30.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	55.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000
50%	80.000000	0.000000	1.000000	0.000000	0.000000	1.000000	1.000000
75%	80.000000	1.000000	1.000000	0.000000	0.000000	1.000000	1.000000
max	80.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

The distribution of the integer variables did not significantly change by dropping the NaN values and the 2 columns. Hence, we can continue our analysis with the new dataset.

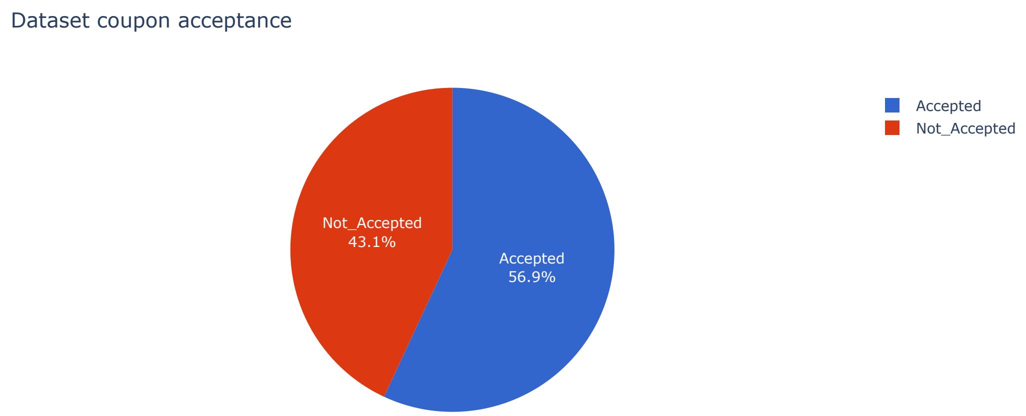
4. What proportion of the total observations chose to accept the coupon?

In [10]:
```
#Determine the proportion of the sample that accepts the coupons
occurence_Y = data_clean['Y'].value_counts()
print(round(occurence_Y[1]/occurence_Y.sum()*100,3), "% of the total sample have accepted the coupons.")
```

```
56.934 % of the total sample have accepted the coupons.
```

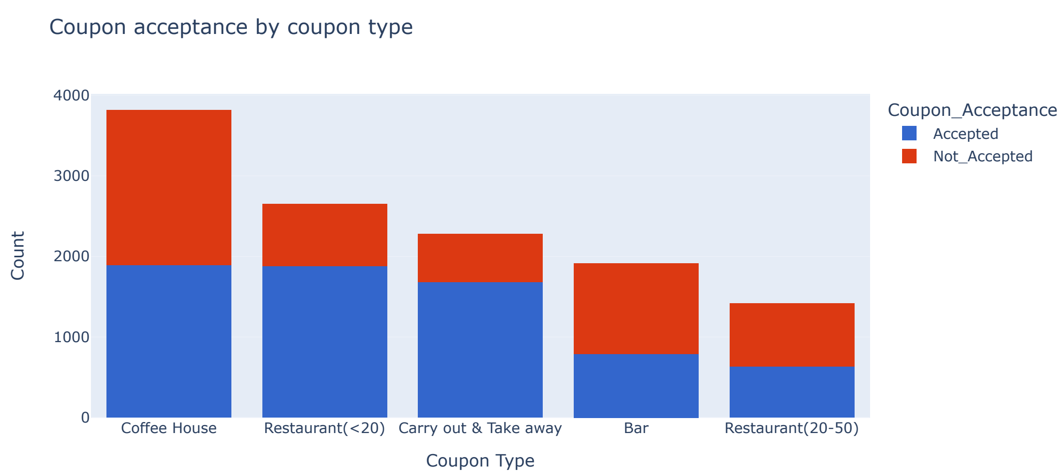
In [11]:
```
#To help with the visualization and labels, we will rename the column and boolean "Y"
data_clean['Coupon_Acceptance']= data_clean['Y'].apply(lambda x: 'Accepted' if x else 'Not_Accepted')
```

In [12]:
```
#Visualize through a pie chart the bar coupon acceptance
pie_clean = px.pie(data_clean, names = 'Coupon_Acceptance', title = 'Dataset coupon acceptance',
                   color_discrete_sequence = px.colors.qualitative.G10, width = 900, height = 450)
pie_clean.update_traces(textposition = 'inside', textinfo = 'percent+label')

pie_clean.show(rendered = 'png')
```



5. Use a bar plot to visualize the `coupon` column.

In [13]:
```
#We will explore the acceptance of coupons by coupon type
fig_coupon = px.histogram(data_clean, x ='coupon',color='Coupon_Acceptance', title = 'Coupon acceptance by coupon type',
                          color_discrete_sequence = px.colors.qualitative.G10, width = 900, height = 450)
fig_coupon.update_xaxes(categoryorder='total descending')
fig_coupon.update_layout(
    xaxis_title='Coupon Type',
    yaxis_title= 'Count')
fig_coupon.show(rendered = 'png')
```



The histogram shows the number of coupons given out per category. We observe that Coffee House has the largest number of coupons (accepted and not accepted) and an overall acceptance of ~50%. At first sight, Restaurant(<20) and Carry out & Take away seem to have a high acceptance ratio. The Bar seem to have the lowest acceptance ratio. The overall acceptance ratio of 56.9% is skewed by the distribution of coupon and it will be important to explore the category seperately to address for other categories pulling the mean away from their True Mean.

In [14]:
```
#We will use a table to numerically observe the coupon acceptance per coupon type
# and better understand the acceptance ratio
Table_data_clean = data_clean.groupby(['coupon', 'Coupon_Acceptance'])[['Coupon_Acceptance']].count()
Table_data_clean['Coupon_%_Per_Category'] = Table_data_clean/Table_data_clean.groupby(level=0).sum()*100
```

```
Table_data_clean['Total_Acceptance_%'] = Table_data_clean['Coupon_Acceptance']/Table_data_clean['Coupon_Acceptance'].sum()*100
Table_data_clean
```

Out[14]:

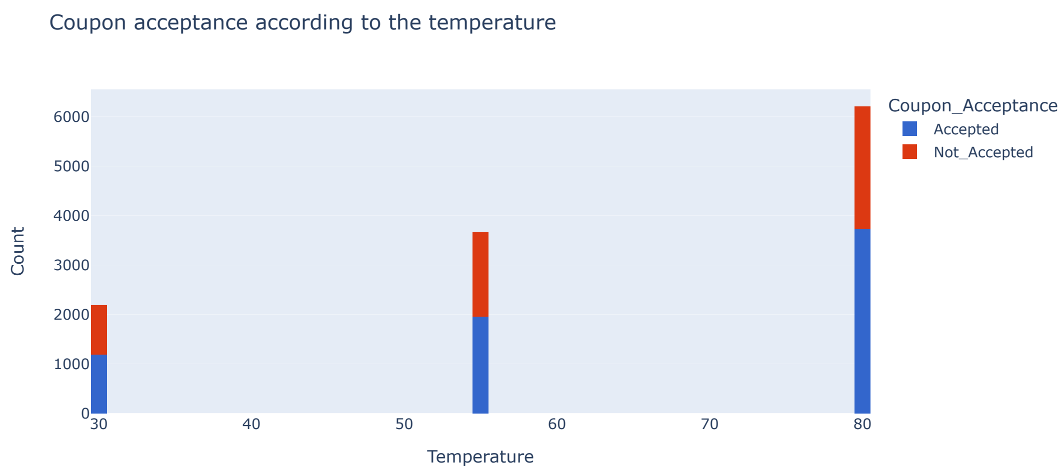
coupon	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Total_Acceptance_%
Bar	Accepted	788	41.191845	6.523719
	Not_Accepted	1125	58.808155	9.313685
Carry out & Take away	Accepted	1682	73.771930	13.924994
	Not_Accepted	598	26.228070	4.950741
Coffee House	Accepted	1894	49.633124	15.680106
	Not_Accepted	1922	50.366876	15.911913
Restaurant(20-50)	Accepted	632	44.601270	5.232221
	Not_Accepted	785	55.398730	6.498882
Restaurant(<20)	Accepted	1881	70.900867	15.572481
	Not_Accepted	772	29.099133	6.391258

Supplementing the histogram with the table, it can be determined that the category 'Carry out & Take away' has the highest acceptance ratio with 73%. Closely followed by 'Restaurant(<20)' with an acceptance ratio of 71%. In contrast, the coupon type 'Bar' had the lowest acceptance with 41%. Coffe House has a 1/2 chance of having a coupon accepted

6. Use a histogram to visualize the temperature column.

In [15]:

```
#Histogram considering acceptance of coupons according to the temperature
fig_temperature = px.histogram(data_clean, x ='temperature',color='Coupon_Acceptance',
                              title = 'Coupon acceptance according to the temperature', nbins=70,
                             color_discrete_sequence = px.colors.qualitative.G10, width = 900, height = 450)
fig_temperature.update_layout(
    xaxis_title='Temperature',
    yaxis_title= 'Count')
fig_temperature.show(rendered = 'png')
```



The histogram does not show a significant difference in the proportion of acceptance according to different temperatures. Increasing coupons were issued as the temperature increased.

In [16]:

```
#We will use a table to numerically observe the coupon acceptance according to temperature
Tbl_temperature = data_clean.groupby(['temperature', 'Coupon_Acceptance'])[['Coupon_Acceptance']].count()
Tbl_temperature['Coupon_%_Per_Category'] = Tbl_temperature/Tbl_temperature.groupby(level=0).sum()*100
Tbl_temperature['Total_Acceptance_%'] = Tbl_temperature['Coupon_Acceptance']/Tbl_temperature['Coupon_Acceptance'].sum()*100
Tbl_temperature
```

Out[16]:

temperature	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Total_Acceptance_%
30	Accepted	1179	53.712984	9.760742
	Not_Accepted	1016	46.287016	8.411292
55	Accepted	1967	53.713818	16.284461
	Not_Accepted	1695	46.286182	14.032619
80	Accepted	3731	59.964642	30.888319
	Not_Accepted	2491	40.035358	20.622568

The acceptance percentage of coupons is roughly 6% greater at the temperature of 80. Acceptance ratio is 54% for temperatures of 55 and 30.

Investigating the Bar Coupons

Now, we will lead you through an exploration of just the bar related coupons.

1. Create a new `DataFrame` that contains just the bar coupons.

In [17]:
```
#We use the clean DataFrame from which we extract the rows where coupon == Bar
data_bar = data_clean[data_clean['coupon']=='Bar']
print(data_bar.shape)
```

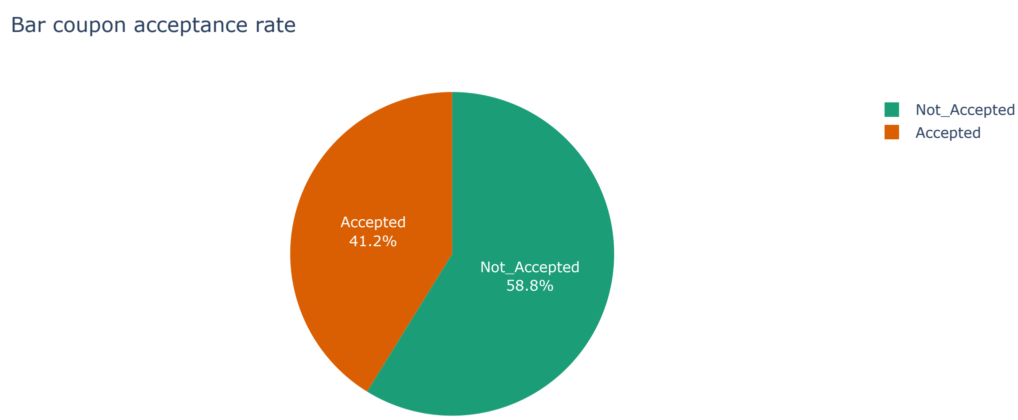
```
(1913, 25)
```

The resulting DataFrame has 1913 observations and 25 columns

2. What proportion of bar coupons were accepted?

Similarly as above we can use the group and count function to answer this question

In [18]:
```
#Visualize through a pie chart the bar coupon acceptance
pie_bar = px.pie(data_bar, names = 'Coupon_Acceptance', title = 'Bar coupon acceptance rate',
                  color_discrete_sequence = px.colors.qualitative.Dark2, width = 900, height = 450)
pie_bar.update_traces(textposition = 'inside', textinfo = 'percent+label')
pie_bar.show(rendered = 'png')
```



We can see that 41.2% of the coupons for Bars were accepted.

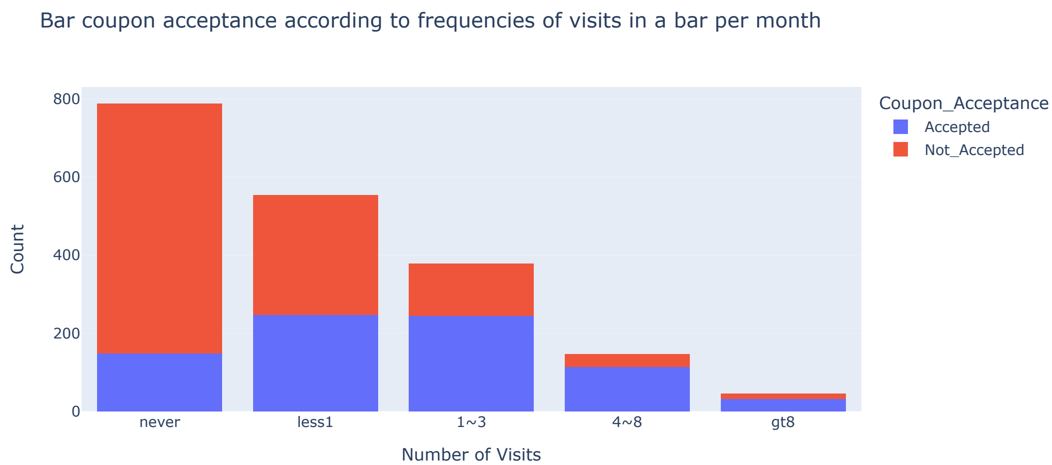
In [19]:
```
#Table to count % of coupon accepted/refused
Tbl_bar_count = data_bar.groupby(['coupon','Coupon_Acceptance'])[['Coupon_Acceptance']].count()
Tbl_bar_count['Bar_Total_Acceptance_%'] = Tbl_bar_count['Coupon_Acceptance']/Tbl_bar_count['Coupon_Acceptance'].sum()*100
Tbl_bar_count
```

Out[19]:

coupon	Coupon_Acceptance	Coupon_Acceptance	Bar_Total_Acceptance_%
Bar	Accepted	788	41.191845
	Not_Accepted	1125	58.808155

3. Compare the acceptance rate between those who went to a bar 3 or fewer times a month to those who went more.

In [20]:
```
#Create a bar chart illustrating the frequency of attendence and acceptance rate
fig_bar = px.histogram(data_bar, x ='Bar',color='Coupon_Acceptance',
                       title = 'Bar coupon acceptance according to frequencies of visits in a bar per month',
                      width = 900, height = 450)
fig_bar.update_xaxes(categoryorder = 'array', categoryarray = ['never','less1', '1~3', '4~8', 'gt8'])
fig_bar.update_layout(
    xaxis_title='Number of Visits',
    yaxis_title= 'Count')
fig_bar.show(rendered = 'png')
```



In [21]:
```
#Create a table to numerically quantify the observations
Tbl_bar_freq = data_bar.groupby(['Bar','Coupon_Acceptance'])[['Coupon_Acceptance']].count()
Tbl_bar_freq['Coupon_%_Per_Freq'] = Tbl_bar_freq/Tbl_bar_freq.groupby(level=0).sum()*100
Tbl_bar_freq['Bar_Total_Acceptance_%'] = Tbl_bar_freq['Coupon_Acceptance']/Tbl_bar_freq['Coupon_Acceptance'].sum()*100
Tbl_bar_freq
```

Out[21]:

Bar	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Freq	Bar_Total_Acceptance_%
1~3	Accepted	245	64.643799	12.807109
	Not_Accepted	134	35.356201	7.004705
4~8	Accepted	114	77.551020	5.959226
	Not_Accepted	33	22.448980	1.725039
gt8	Accepted	33	71.739130	1.725039
	Not_Accepted	13	28.260870	0.679561
less1	Accepted	247	44.665461	12.911657
	Not_Accepted	306	55.334539	15.995818
never	Accepted	149	18.908629	7.788813
	Not_Accepted	639	81.091371	33.403032

The acceptance rate seem to increase as the frequency of visits increases. The acceptance rate achieved 64.64% or higher starting with people visiting a bar a minimum of once a month. The average bar coupon acceptance of 41.2% is impacted by the large number of people never or rarely attending bars. Hence, acceptance of a bar coupon is largely reliant on the monthly attendance. The success rate of coupons becomes interesting for visitors of 1~3 and greater. In contrast those who never go to the bar accept the coupon 19% of the time.

4. Compare the acceptance rate between drivers who go to a bar more than once a month and are over the age of 25 to the all others. Is there a difference?

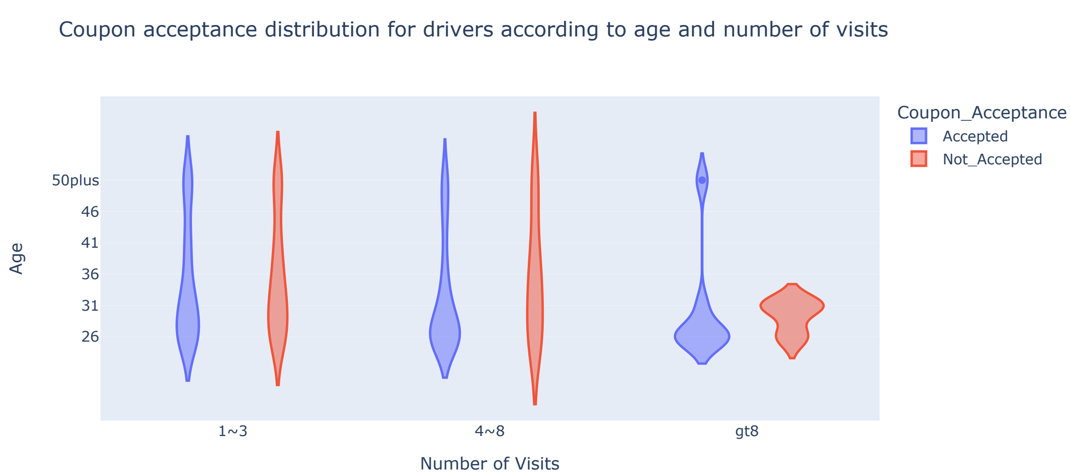
In [22]:
```
#Create list criteria to filter the table
List_Visits = ["1~3", "4~8", "gt8"]
List_Age = ["26", "31","36","41","46","50plus"]

#Create a subset that meet the criteria. This group will be group1.
data_bar_visits = data_bar[data_bar['Bar'].isin(List_Visits)]
data_bar_visits_Age = data_bar_visits[data_bar_visits['age'].isin(List_Age)]

#Table summarizing the group1
Tbl_bar_group1 = data_bar_visits_Age.groupby(['Bar', 'age' ,'Coupon_Acceptance'])[['Coupon_Acceptance']].count()
Tbl_bar_group1['Coupon_%_Per_Category'] = Tbl_bar_group1/Tbl_bar_group1.groupby(['Bar', 'age']).sum()*100
Tbl_bar_group1['Total Acceptance %'] = Tbl_bar_group1['Coupon_Acceptance']/Tbl_bar_group1['Coupon_Acceptance'].sum()*100
Tbl_bar_group1
```

Out[22]:

Bar	age	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Total Acceptance %
1~3	26	Accepted	63	70.786517	15.632754
		Not_Accepted	26	29.213483	6.451613
	31	Accepted	44	64.705882	10.918114
		Not_Accepted	24	35.294118	5.955335
	36	Accepted	14	50.000000	3.473945
		Not_Accepted	14	50.000000	3.473945
	41	Accepted	18	64.285714	4.466501
		Not_Accepted	10	35.714286	2.481390
	46	Accepted	6	66.666667	1.488834
		Not_Accepted	3	33.333333	0.744417
	50plus	Accepted	31	64.583333	7.692308
		Not_Accepted	17	35.416667	4.218362
4~8	26	Accepted	44	84.615385	10.918114
		Not_Accepted	8	15.384615	1.985112
	31	Accepted	14	87.500000	3.473945
		Not_Accepted	2	12.500000	0.496278
	36	Accepted	6	50.000000	1.488834
		Not_Accepted	6	50.000000	1.488834
	41	Accepted	3	75.000000	0.744417
		Not_Accepted	1	25.000000	0.248139
	46	Accepted	6	85.714286	1.488834
		Not_Accepted	1	14.285714	0.248139
	50plus	Accepted	8	66.666667	1.985112
		Not_Accepted	4	33.333333	0.992556
gt8	26	Accepted	15	83.333333	3.722084
		Not_Accepted	3	16.666667	0.744417
	31	Accepted	3	33.333333	0.744417
		Not_Accepted	6	66.666667	1.488834
	50plus	Accepted	3	100.000000	0.744417

There are no clear trends across age groups. We will explore the distribution of each Bar Visit subsets to get a better understanding of its composition.

In [23]:
```
#Create a bar chart illustrating the frequency of attendence and acceptance rate
fig_vio_group1 = px.violin(data_bar_visits_Age, x ='Bar',y='age', color='Coupon_Acceptance',
                       title = 'Coupon acceptance distribution for drivers according to age and number of visits',
                      width = 900, height = 450)
fig_vio_group1.update_xaxes(categoryorder = 'array', categoryarray = ['1~3', '4~8', 'gt8'])
fig_vio_group1.update_yaxes(categoryorder='category ascending')
fig_vio_group1.update_layout(
    xaxis_title='Number of Visits',
    yaxis_title= 'Age')
fig_vio_group1
```



The graph offer great insight on the distribution of the groups. The age 41 and 46 are the 'skinniest' part of the violin. Indicating, they were the least present in the sample. Hence, they could be underepresented. For instance, they were absent in the sample of visits greater than 8 times. The 50plus age group attending the bar greater than 8 times a month accepted all coupons. The people aged 26 attending the bar greater than 8 times accept 83% of coupons offered to them. This subset seems to accept coupons very often if they visit a bar 4 months or more a month.

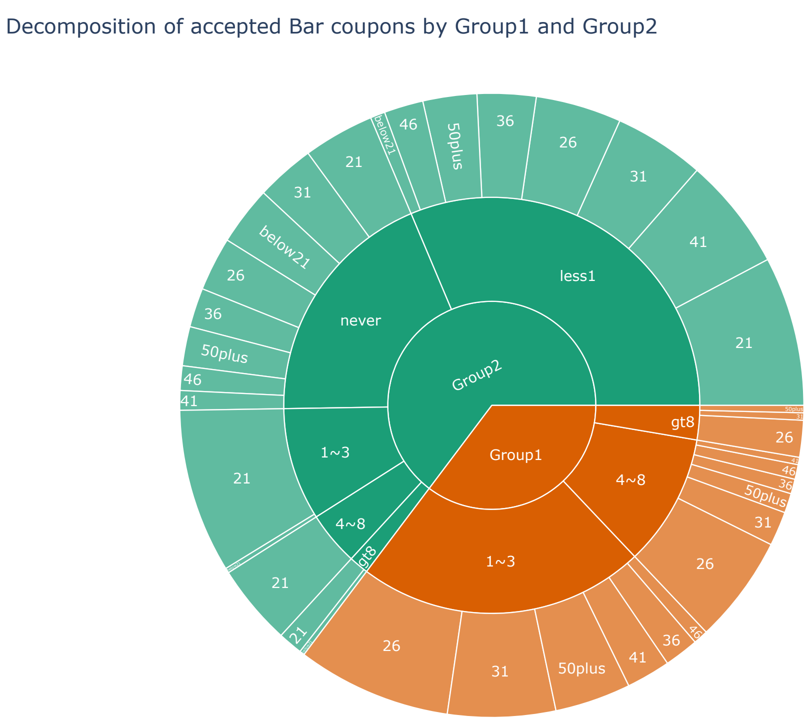
In [24]:
```
#The leftover dataset will be referred to as group2
df_bar_merge = data_bar.merge(data_bar_visits_Age, how='left', indicator = True)
df_bar_left = df_bar_merge[df_bar_merge['_merge']== 'left_only']

Tbl_bar_group2 = df_bar_left.groupby(['Bar', 'age' ,'Coupon_Acceptance'])[['Coupon_Acceptance']].count()
Tbl_bar_group2['Coupon_%_Per_Category'] = Tbl_bar_group2/Tbl_bar_group2.groupby(['Bar', 'age']).sum()*100
Tbl_bar_group2['Total Acceptance %'] = Tbl_bar_group2['Coupon_Acceptance']/Tbl_bar_group2['Coupon_Acceptance'].sum()*100
Tbl_bar_group2.head()
```

Out[24]:

Bar	age	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Total Acceptance %
1~3	21	Accepted	67	65.048544	4.437086
		Not_Accepted	36	34.951456	2.384106
	below21	Accepted	2	33.333333	0.132450
		Not_Accepted	4	66.666667	0.264901
4~8	21	Accepted	33	75.000000	2.185430

To better understand the acceptance of coupon according to the number of visits and age, we will create a sunburst chart representing all accepted coupon and coloring Group1 and Group2

In [25]:
```
#replace labels so they become meaningful
df_bar_merge['Group']= df_bar_merge['_merge'].apply(lambda x: 'Group2' if x == 'left_only' else 'Group1')

#sunburst chart to better understand the breakdown of the bar dataset
fig_sun_bar = px.sunburst(df_bar_merge, path = ['Group','Bar','age'], values='Y',
                          title = 'Decomposition of accepted Bar coupons by Group1 and Group2',
                     color_discrete_sequence = px.colors.qualitative.Dark2, width = 900, height = 700 )
fig_sun_bar.show(rendered = 'png')
```



Group1 accounts for roughly 35% of total accepted coupons and the majority of the subset is composed of people attending the bar 1~3 times a month. The age group accepting the most coupons in group 1 are 26 years of age. In contrast, the majority of group2 is composed of people who did not or rarely attend the bar and accepted coupons.

In [26]:
```
#Determine the proportion of the sample that accepts the coupons
#Group1
occurence_Y_group1 = data_bar_visits_Age['Y'].value_counts()
print("Group1:",round(occurence_Y_group1[1]/occurence_Y_group1.sum()*100,3), "% of the total sample have accepted the coupons.")

#Group2
occurence_Y_group2 = df_bar_left['Y'].value_counts()
print("Group2:",round(occurence_Y_group2[1]/occurence_Y_group2.sum()*100,3), "% of the total sample have accepted the coupons.")
```

```
Group1: 68.983 % of the total sample have accepted the coupons.
Group2: 33.775 % of the total sample have accepted the coupons.
```

The acceptance rate of group1 is much higher than the group2 meaning that people older than 25 that often go to a bar have a 66% chance of accepting a coupon. In contrast, younger or people not attending the bar often accept a bar coupon 37% of the time.

5. Use the same process to compare the acceptance rate between drivers who go to bars more than once a month and had passengers that were not a kid and had occupations other than farming, fishing, or forestry.

In [27]:
```
#Create list criteria to filter the table
List_Visits = ["1~3", "4~8", "gt8"]
List_Passanger = ["Friend(s)", "Partner"]
List_Not_Occupation = ["Farming Fishing & Forestry"]
```

In [28]:
```
data_bar_MoreOne = data_bar[data_bar['Bar'].isin(List_Visits)]
data_bar_MoreOne_wPassanger = data_bar_MoreOne[data_bar_MoreOne['passanger'].isin(List_Passanger)]
data_bar_MoreOne_wPassanger_OtherOcc = data_bar_MoreOne_wPassanger[-data_bar_MoreOne_wPassanger['occupation'].isin(List_Not_Occupation)]

Tbl_group_OtherOcc = data_bar_MoreOne_wPassanger_OtherOcc.groupby(['occupation',
                                                   'Bar','passanger','Coupon_Acceptance'])[['Coupon_Acceptance']].count()
Tbl_group_OtherOcc['Coupon_%_Per_Category'] = Tbl_group_OtherOcc/Tbl_group_OtherOcc.groupby(['occupation',
                                                                    'Bar', 'passanger']).sum()*100
Tbl_group_OtherOcc['Acceptance %'] = Tbl_group_OtherOcc['Coupon_Acceptance']/Tbl_group_OtherOcc['Coupon_Acceptance'].sum()*100
Tbl_group_OtherOcc.head()
```

Out[28]:

occupation	Bar	passanger	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Acceptance %
Architecture & Engineering	1~3	Friend(s)	Accepted	2	100.0	1.058201
		Partner	Accepted	1	100.0	0.529101
Arts Design Entertainment Sports & Media	1~3	Friend(s)	Accepted	2	100.0	1.058201
		Partner	Accepted	1	100.0	0.529101
	4~8	Friend(s)	Not_Accepted	1	100.0	0.529101

In [29]:
```
#The leftover dataset will be referred to as
df_bar_all = data_bar.merge(data_bar_MoreOne_wPassanger_OtherOcc, how='left', indicator = True)
df_bar_allOcc = df_bar_all[df_bar_all['_merge']== 'left_only']

Tbl_group_allOcc = df_bar_allOcc.groupby(['occupation',
                                                   'Bar','passanger','Coupon_Acceptance'])[['Coupon_Acceptance']].count()
Tbl_group_allOcc['Coupon_%_Per_Category'] = Tbl_group_allOcc/Tbl_group_allOcc.groupby(['occupation',
                                                                    'Bar', 'passanger']).sum()*100
Tbl_group_allOcc['Acceptance %'] = Tbl_group_allOcc['Coupon_Acceptance']/Tbl_group_allOcc['Coupon_Acceptance'].sum()*100
Tbl_group_allOcc.head()
```

Out[29]:

occupation	Bar	passanger	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Acceptance %
Architecture & Engineering	1~3	Alone	Accepted	3	100.000000	0.174014
	less1	Alone	Accepted	5	55.555556	0.290023
			Not_Accepted	4	44.444444	0.232019
		Kid(s)	Not_Accepted	2	100.000000	0.116009
		Partner	Accepted	3	75.000000	0.174014

In [30]:
```
#Determine the proportion of the sample that accepts the coupons
#Group1
occurence_Y_OtherOcc = data_bar_MoreOne_wPassanger_OtherOcc['Y'].value_counts()
print("Group_OtherOcc_wPass:",round(occurence_Y_OtherOcc[1]/occurence_Y_OtherOcc.sum()*100,3), "% of the total sample have accepted the coupons.")

#Group2
occurence_Y_allOcc = df_bar_allOcc['Y'].value_counts()
print("Group_allOcc:",round(occurence_Y_allOcc[1]/occurence_Y_allOcc.sum()*100,3), "% of the total sample have accepted the coupons.")
```

```
Group_OtherOcc_wPass: 71.429 % of the total sample have accepted the coupons.
Group_allOcc: 37.877 % of the total sample have accepted the coupons.
```

With 71.43% acceptance rate, people with passengers that are not farmers are much more likely to accept coupons in contrast to those without passengers or farmers.

6. Compare the acceptance rates between those drivers who:

- go to bars more than once a month, had passengers that were not a kid, and were not widowed *OR*
- go to bars more than once a month and are under the age of 30 *OR*
- go to cheap restaurants more than 4 times a month and income is less than 50K.

In [31]:
```
#Create list criteria to filter the table point 1
List_Visits = ["1~3", "4~8", "gt8"]
List_Passanger = ["Friend(s)", "Partner"]
List_Not_Widowed = ["Widowed"]

#Create Dataset
data_bar_MoreOne = data_bar[data_bar['Bar'].isin(List_Visits)]
data_bar_MoreOne_wPassanger = data_bar_MoreOne[data_bar_MoreOne['passanger'].isin(List_Passanger)]
data_bar_MoreOne_wPassanger_NotWid = data_bar_MoreOne_wPassanger[-data_bar_MoreOne_wPassanger
                                                     ['maritalStatus'].isin(List_Not_Widowed)]
#Measure Acceptance
df_bar_Point1 = data_bar_MoreOne_wPassanger_NotWid.groupby(['Bar', 'passanger' ,
```

```
                                          'maritalStatus', 'Coupon_Acceptance'])[['Coupon_Acceptance']].count()
df_bar_Point1['Coupon_%_Per_Category'] = df_bar_Point1/df_bar_Point1.groupby(['Bar', 'passanger', 'maritalStatus']).sum()*100
df_bar_Point1['Total Acceptance %'] = df_bar_Point1['Coupon_Acceptance']/df_bar_Point1['Coupon_Acceptance'].sum()*100
df_bar_Point1.head()
```

Out[31]:

Bar	passanger	maritalStatus	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Total Acceptance %
1~3	Friend(s)	Divorced	Accepted	2	66.666667	1.058201
			Not_Accepted	1	33.333333	0.529101
		Married partner	Accepted	15	71.428571	7.936508
			Not_Accepted	6	28.571429	3.174603
		Single	Accepted	33	84.615385	17.460317

In [32]:

```
#Create list criteria to filter the table point 2
List_Visits = ["1~3", "4~8", "gt8"]
List_Age = ["below21", "21", "26"]

#Create Dataset
data_bar_MoreOne_p2 = data_bar[data_bar['Bar'].isin(List_Visits)]
data_bar_MoreOne_b30 = data_bar_MoreOne_p2[data_bar_MoreOne_p2['age'].isin(List_Age)]

#Measure Acceptance
df_bar_Point2 = data_bar_MoreOne_b30.groupby(['Bar', 'age', 'Coupon_Acceptance'])[['Coupon_Acceptance']].count()
df_bar_Point2['Coupon_%_Per_Category'] = df_bar_Point2/df_bar_Point2.groupby(['Bar','age']).sum()*100
df_bar_Point2['Total Acceptance %'] = df_bar_Point2['Coupon_Acceptance']/df_bar_Point1['Coupon_Acceptance'].sum()*100
df_bar_Point2.head()
```

Out[32]:

Bar	age	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Total Acceptance %
1~3	21	Accepted	67	65.048544	35.449735
		Not_Accepted	36	34.951456	19.047619
	26	Accepted	63	70.786517	33.333333
		Not_Accepted	26	29.213483	13.756614
	below21	Accepted	2	33.333333	1.058201

In [33]:

```
#Create list criteria to filter the table point 1
List_Visit_Rest = ["4~8", "gt8"]
List_Income = ["Less than $12500", "$12500 - $24999", "$25000 - $37499", "$37500 - $49999"]


#Create Dataset
data_rest_MoreOne = data_bar[data_bar['RestaurantLessThan20'].isin(List_Visit_Rest)]
data_rest_MoreOne_w50k = data_rest_MoreOne[data_rest_MoreOne['income'].isin(List_Income)]


#Measure Acceptance
df_rest_Point3 = data_rest_MoreOne_w50k.groupby(['RestaurantLessThan20',
                                            'income', 'Coupon_Acceptance'])[['Coupon_Acceptance']].count()
df_rest_Point3['Coupon_%_Per_Category'] = df_rest_Point3/df_rest_Point3.groupby(['RestaurantLessThan20', 'income']).sum()*100
df_rest_Point3['Total Acceptance %'] = df_rest_Point3['Coupon_Acceptance']/df_rest_Point3['Coupon_Acceptance'].sum()*100
df_rest_Point3
```

Out[33]:

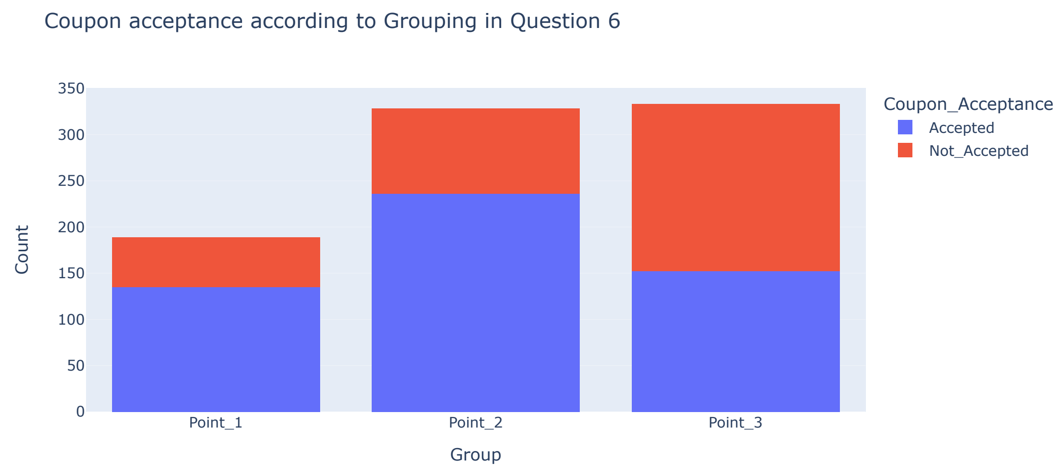
RestaurantLessThan20	income	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Total Acceptance %
4~8	12500−24999	Accepted	30	41.666667	9.009009
		Not_Accepted	42	58.333333	12.612613
	25000−37499	Accepted	25	43.859649	7.507508
		Not_Accepted	32	56.140351	9.609610
	37500−49999	Accepted	20	40.000000	6.006006
		Not_Accepted	30	60.000000	9.009009
	Less than $12500	Accepted	20	34.482759	6.006006
		Not_Accepted	38	65.517241	11.411411
gt8	12500−24999	Accepted	11	45.833333	3.303303
		Not_Accepted	13	54.166667	3.903904
	25000−37499	Accepted	8	47.058824	2.402402
		Not_Accepted	9	52.941176	2.702703
	37500−49999	Accepted	26	65.000000	7.807808
		Not_Accepted	14	35.000000	4.204204
	Less than $12500	Accepted	12	80.000000	3.603604
		Not_Accepted	3	20.000000	0.900901

In [34]:

```
#Compare each group/point with the leftover data points
#Define the groups
data_bar_MoreOne_wPassanger_NotWid['Group']=data_bar_MoreOne_wPassanger_NotWid.apply(lambda x:'Point_1', axis = 1)
data_bar_MoreOne_b30['Group']=data_bar_MoreOne_b30.apply(lambda x:'Point_2', axis = 1)
```

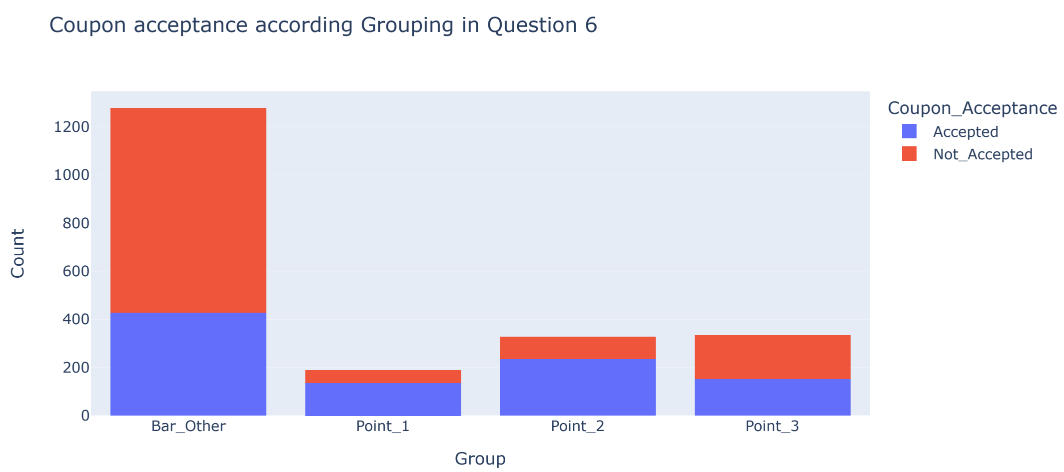
```
data_rest_MoreOne_w50k['Group']=data_rest_MoreOne_w50k.apply(lambda x:'Point_3', axis = 1)

#We will incrementally merge each dataframe to detect rows that are present in many df
df_point_1_2 = data_bar_MoreOne_wPassanger_NotWid.merge(data_bar_MoreOne_b30, how='outer', indicator = True)
df_point_1_2.loc[(df_point_1_2._merge == 'both'), 'Group'] = 'Point_1_2'
df_point_1_2 = df_point_1_2.drop(['_merge'], axis=1)

df_point_1_2_3 = df_point_1_2.merge(data_rest_MoreOne_w50k, how='outer', indicator = True)
df_point_1_2_3.loc[(df_point_1_2_3._merge == 'both'), 'Group'] = 'Point_1_2_3'
df_point_1_2_3 = df_point_1_2_3.drop(['_merge'], axis=1)
print(df_point_1_2_3['Group'].unique())

#illustrate the acceptance amongst point groups
fig_Points = px.histogram(df_point_1_2_3, x ='Group',color='Coupon_Acceptance',
                       title = 'Coupon acceptance according to Grouping in Question 6',
                      width = 900, height = 450)

fig_Points.update_layout(
    xaxis_title='Group',
    yaxis_title= 'Count')
fig_Points.show(rendered = 'png')
```

```
['Point_1' 'Point_2' 'Point_3']
```



In [35]:
```
#Now we will merge with the data_clean to compare the behavior of all
df_point_nBar = data_bar.merge(df_point_1_2_3, how='outer', indicator = True)
df_point_nBar.loc[(df_point_nBar._merge != 'both'), 'Group'] = 'Bar_Other'
df_point_nBar = df_point_nBar.drop(['_merge'], axis=1)
print(df_point_nBar['Group'].unique())
print(df_point_nBar.shape)

#To illustrate our findings we will make a histogram
fig_Point_nBar = px.histogram(df_point_nBar, x ='Group',color='Coupon_Acceptance',
                       title = 'Coupon acceptance according Grouping in Question 6',
                      width = 900, height = 450)

fig_Point_nBar.update_layout(
    xaxis_title='Group',
    yaxis_title= 'Count')
fig_Point_nBar.show(rendered = 'png')
```

```
['Bar_Other' 'Point_1' 'Point_2' 'Point_3']
(2128, 26)
```



In [36]:
```
#We numerically explore our findings
num_point_nBar = df_point_nBar.groupby(['Group','Coupon_Acceptance'])[['Coupon_Acceptance']].count()
num_point_nBar['Coupon_%_Per_Category'] = num_point_nBar/num_point_nBar.groupby(['Group']).sum()*100
num_point_nBar['Total Acceptance %'] = num_point_nBar['Coupon_Acceptance']/num_point_nBar['Coupon_Acceptance'].sum()*100
num_point_nBar
```

Out[36]:

Group	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Total Acceptance %
Bar_Other	Accepted	428	33.489828	20.112782
	Not_Accepted	850	66.510172	39.943609
Point_1	Accepted	135	71.428571	6.343985
	Not_Accepted	54	28.571429	2.537594
Point_2	Accepted	236	71.951220	11.090226
	Not_Accepted	92	28.048780	4.323308
Point_3	Accepted	152	45.645646	7.142857
	Not_Accepted	181	54.354354	8.505639

Our numerical analysis provides insight in the acceptance rate of the 3 groups. The 3 groups selected are more probable of accepting a coupon than their counterparts in the bar group. Recall bar coupon acceptance is roughly 42%. Interestingly, Point_1 and Point_2 is much more likely to accept coupons. The commonality amongst these two groups is the number of visits is greater than once a month. This may indicate that frequency at which a person visits the bar monthly greatly affects its probability to accept such coupons. Furthermore, it indicates that people visiting restaurants more than 4 times a week are less likely to redeem bar coupons.

7. Based on these observations, what do you hypothesize about drivers who accepted the bar coupons?

According to the following:

1. The more often people went to the bar, the more likely they were to redeem a coupon.
2. Of all accepted coupons, those who went to the bar less1 and never accounted for ~50%
3. In those who frequented the bar more than once a month, the age group of 26 was the most likely to accept a coupon. In general, age did not inherintely impact the acceptance ratio.
4. People visiting the bar more than once with passangers and who are not farmers are much more likely to accept coupons than their counterparts.
5. People who attended cheap restaurants more than 4 times a month and had an income lower than 50k were less likely to accept a coupon than people frequently visiting a bar. But were more likely than the rest of the dataset.
6. People with passanger that were widowed were not more likely to accept coupons than people with passengers.

I hypothesize that:

- The more often people went to the bar, the more likely they were to redeem a coupon.
- The age group of 26 is the most likely to accept coupons
- People with passenger are more likely to accept coupons
- If people are frequently attending other categories of stores, they are less likely to accept coupons than those frequently attending the bar.

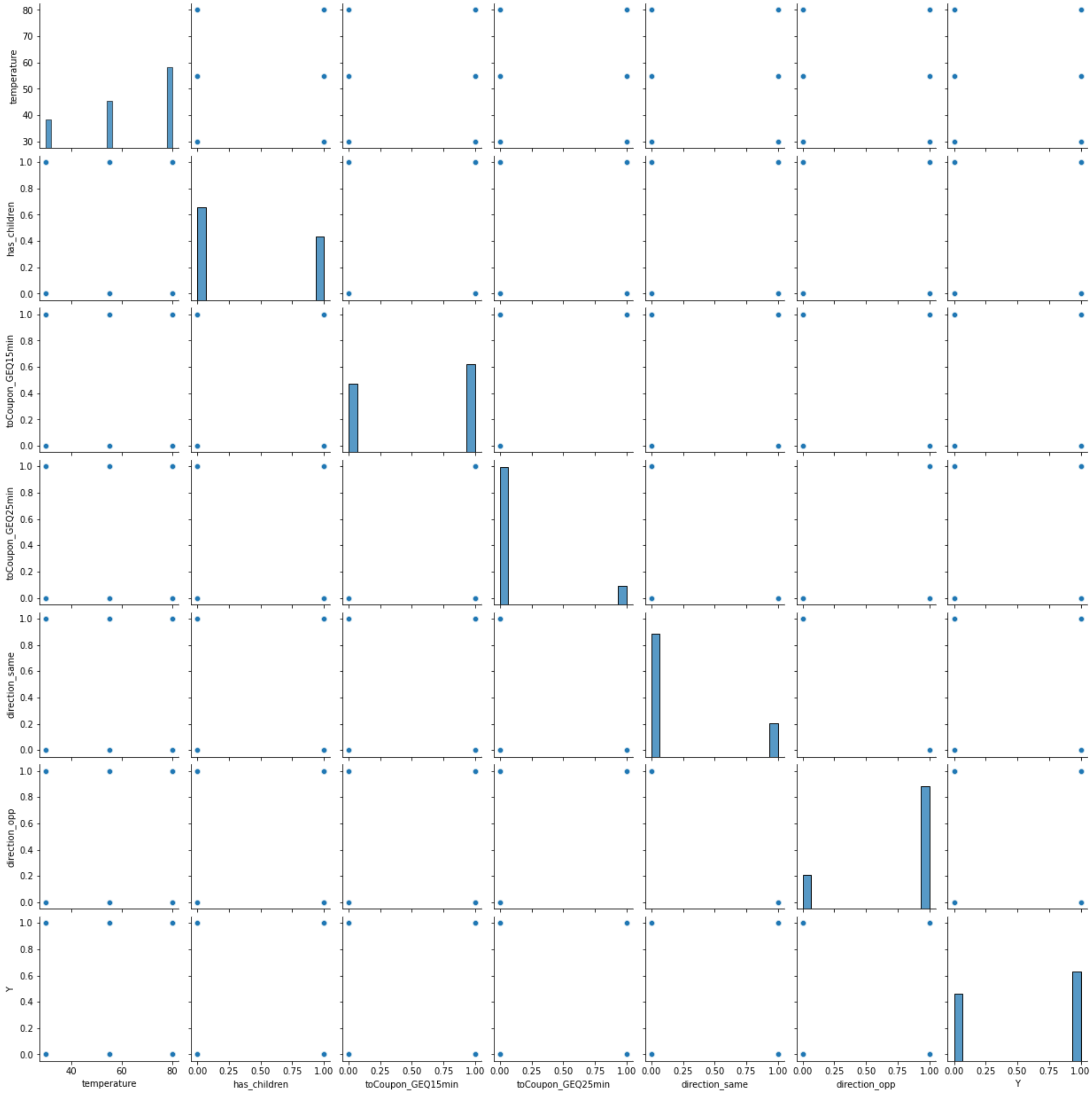
Independent Investigation

Using the bar coupon example as motivation, you are to explore one of the other coupon groups and try to determine the characteristics of passengers who accept the coupons.

To begin my exploration, I would like to explore the correlation amongst integer variables.

In [37]:
```
sns.pairplot(data_clean)
```

Out[37]:
```
<seaborn.axisgrid.PairGrid at 0x23f03f07b50>
```



We can see that all integer variables are not continuouse and exploring for correlations with scatter plots will be hard since that are grouped in categories. Hence, we will focus our investigation through bar charts and histograms.

Looking back at the table expressing the % acceptance per coupon class, I chose to investigate the Coffee House since their acceptance were close to 50% which I believe was low considering the popularity of Coffee.

In [38]:
```
#Similarly to the bar dataset, I will create a Coffee dataset.
data_coffee = data_clean[data_clean['coupon']=='Coffee House']
print(data_coffee.shape)
data_coffee.head(5)
```

```
(3816, 25)
```

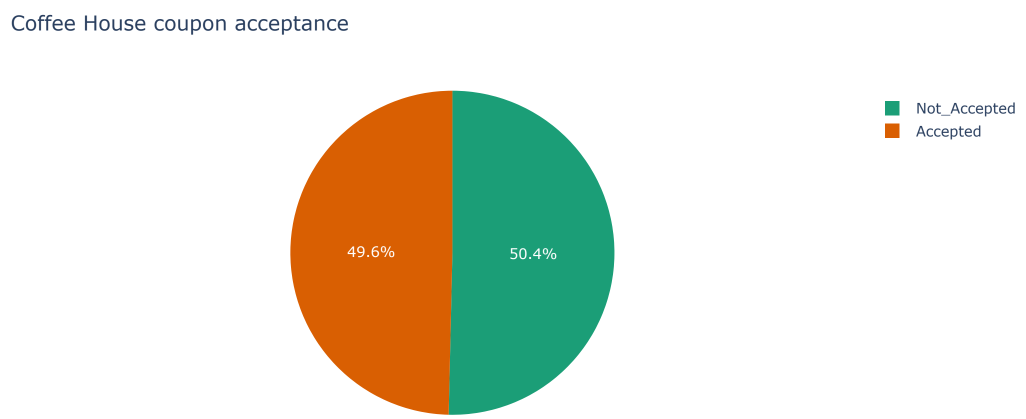
Out[38]:

	destination	passanger	weather	temperature	time	coupon	expiration	gender	age	maritalStatus	...	CoffeeHouse	CarryAway	RestaurantLessThan20	Restaurant20To50	toC
23	No Urgent Place	Friend(s)	Sunny	80	10AM	Coffee House	2h	Male	21	Single	...	less1	4~8	4~8	less1	
26	No Urgent Place	Friend(s)	Sunny	80	2PM	Coffee House	1d	Male	21	Single	...	less1	4~8	4~8	less1	
27	No Urgent Place	Friend(s)	Sunny	80	2PM	Coffee House	2h	Male	21	Single	...	less1	4~8	4~8	less1	
28	No Urgent Place	Friend(s)	Sunny	80	2PM	Coffee House	1d	Male	21	Single	...	less1	4~8	4~8	less1	
30	No Urgent Place	Friend(s)	Sunny	80	6PM	Coffee House	2h	Male	21	Single	...	less1	4~8	4~8	less1	

5 rows × 25 columns

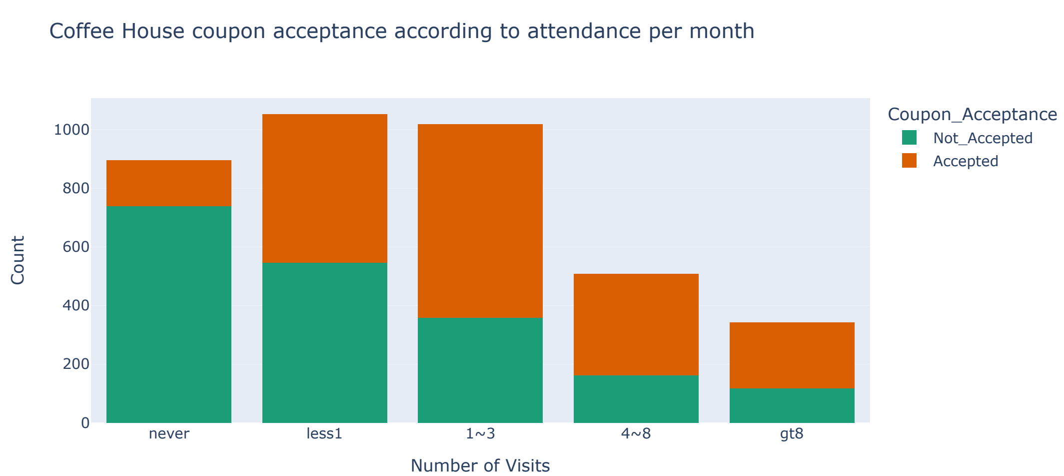
The coffee dataset has 3,816 observations.

In [39]:
```
#Visualize through a pie chart the coupon acceptance
pie_coffee = px.pie(data_coffee, names = 'Coupon_Acceptance', title = 'Coffee House coupon acceptance',
                    color_discrete_sequence = px.colors.qualitative.Dark2, width = 900, height = 450)
pie_coffee.show(rendered = 'png')
```



1. We will explore the coupon acceptance by frequency of visits

In [40]:
```
#Create a bar chart illustrating the frequency of attendence and acceptance rate
fig_coffee = px.histogram(data_coffee, x ='CoffeeHouse',color='Coupon_Acceptance',
                       title = 'Coffee House coupon acceptance according to attendance per month',
                     color_discrete_sequence = px.colors.qualitative.Dark2, width = 900, height = 450)
fig_coffee.update_xaxes(categoryorder = 'array', categoryarray = ['never','less1', '1~3', '4~8', 'gt8'])
fig_coffee.update_layout(
    xaxis_title='Number of Visits',
    yaxis_title= 'Count')
fig_coffee.show(rendered = 'png')
```



Similarly to Bar coupon, the higher the number of visits the more likely the use of a Coffee House coupon. The less1 and 1~3 frequency were the most present in the sample.

In [41]:
```
#Create a table to numerically quantify the graph above
Tbl_coffee_freq = data_coffee.groupby(['CoffeeHouse','Coupon_Acceptance'])[['Coupon_Acceptance']].count()
Tbl_coffee_freq['Coupon_%_Per_Freq'] = Tbl_coffee_freq/Tbl_coffee_freq.groupby(level=0).sum()*100
Tbl_coffee_freq['Bar_Total_Acceptance_%'] = Tbl_coffee_freq['Coupon_Acceptance']/Tbl_coffee_freq['Coupon_Acceptance'].sum()*100
Tbl_coffee_freq
```

Out[41]:

CoffeeHouse	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Freq	Bar_Total_Acceptance_%
1~3	Accepted	660	64.769382	17.295597
	Not_Accepted	359	35.230618	9.407757
4~8	Accepted	346	68.244576	9.067086
	Not_Accepted	161	31.755424	4.219078
gt8	Accepted	225	65.789474	5.896226
	Not_Accepted	117	34.210526	3.066038
less1	Accepted	506	48.098859	13.259958
	Not_Accepted	546	51.901141	14.308176
never	Accepted	157	17.522321	4.114256
	Not_Accepted	739	82.477679	19.365828

We can notice that the acceptance rate varies importantly between those who frequently visit the coffee house and those who visit a coffee house <1 time a month. Hence, number of visits is an important factor for the acceptance of a coffee house coupon. With the frequency 4~8 having the highest acceptance rate of 68.24%

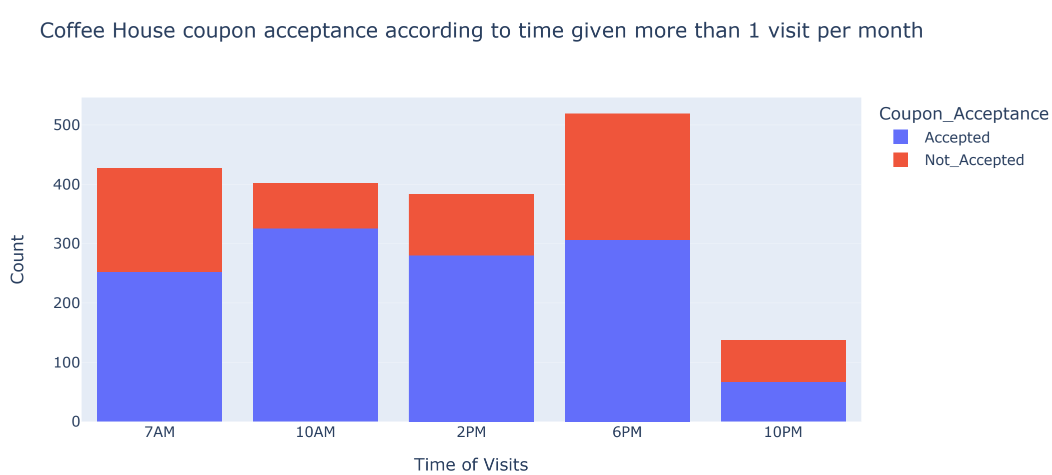
2. Focus on the dataset with visits greater than 1 a month

In [42]:
```
#Create list criteria to filter the table
List_Visits_Coffee = ["1~3", "4~8", "gt8"]

#Create Dataset
data_coffee_MoreOne = data_coffee[data_coffee['CoffeeHouse'].isin(List_Visits_Coffee)]
data_coffee_MoreOne.shape
```

Out[42]: (1868, 25)

3. We will explore the impact of the Time for people frequenting the Coffee House more than once a month

In [43]:
```
#Make a bar chart to explore the distribution and acceptance of the sample
fig_coffee_time = px.histogram(data_coffee_MoreOne, x ='time',color='Coupon_Acceptance',
                        title = 'Coffee House coupon acceptance according to time given more than 1 visit per month',
                       width = 900, height = 450)
fig_coffee_time.update_xaxes(categoryorder = 'array', categoryarray = ['7AM','10AM', '2PM', '6PM', '10PM'])
fig_coffee_time.update_layout(
    xaxis_title='Time of Visits',
    yaxis_title= 'Count')
fig_coffee_time.show(rendered = 'png')
```



We can notice a distribution much more equal. Other than the 10 PM category, there are fairly equal in appearances.

In [44]:
```
#Measure Acceptance Numerically
df_coffe_MoreOne_Time = data_coffee_MoreOne.groupby(['CoffeeHouse','time','Coupon_Acceptance'])[['Coupon_Acceptance']].count()
df_coffe_MoreOne_Time['Coupon_%_Per_Category'] = df_coffe_MoreOne_Time/df_coffe_MoreOne_Time.groupby(['CoffeeHouse', 'time']).sum()*100
df_coffe_MoreOne_Time['Total Acceptance %'] = df_coffe_MoreOne_Time['Coupon_Acceptance']/df_coffe_MoreOne_Time['Coupon_Acceptance'].sum()*100
df_coffe_MoreOne_Time
```

Out[44]:

CoffeeHouse	time	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Total Acceptance %
1~3	10AM	Accepted	173	80.465116	9.261242
		Not_Accepted	42	19.534884	2.248394
	10PM	Accepted	31	53.448276	1.659529
		Not_Accepted	27	46.551724	1.445396
	2PM	Accepted	168	75.000000	8.993576
		Not_Accepted	56	25.000000	2.997859
	6PM	Accepted	164	56.164384	8.779443
		Not_Accepted	128	43.835616	6.852248
	7AM	Accepted	124	53.913043	6.638116
		Not_Accepted	106	46.086957	5.674518
4~8	10AM	Accepted	93	82.300885	4.978587
		Not_Accepted	20	17.699115	1.070664
	10PM	Accepted	27	60.000000	1.445396
		Not_Accepted	18	40.000000	0.963597
	2PM	Accepted	61	64.210526	3.265525
		Not_Accepted	34	35.789474	1.820128
	6PM	Accepted	92	65.248227	4.925054
		Not_Accepted	49	34.751773	2.623126
	7AM	Accepted	73	64.601770	3.907923
		Not_Accepted	40	35.398230	2.141328
gt8	10AM	Accepted	60	81.081081	3.211991
		Not_Accepted	14	18.918919	0.749465
	10PM	Accepted	9	26.470588	0.481799
		Not_Accepted	25	73.529412	1.338330
	2PM	Accepted	51	79.687500	2.730193
		Not_Accepted	13	20.312500	0.695931
	6PM	Accepted	50	58.139535	2.676660
		Not_Accepted	36	41.860465	1.927195
	7AM	Accepted	55	65.476190	2.944325
		Not_Accepted	29	34.523810	1.552463

When looking numerically, we can see that 10 AM and 2PM are the most accepted times amongst these 3 level of visits. 2Pm does not seem significant for 4~8 people. It is clear that Time is an important factor for the acceptance of coupons.

Let's focus on the most successful time (10AM-2PM)

In [45]:
```
#Create list criteria to filter the table
List_Time_Coffee = ["10AM", "2PM"]

#Create Dataset
data_coffee_MoreOne_time = data_coffee_MoreOne[data_coffee_MoreOne['time'].isin(List_Time_Coffee)]
data_coffee_MoreOne_time.shape
```

Out[45]:
```
(785, 25)
```

4. Explore impact of direction given more than 1 visit

In [46]:
```
data_coffee_MoreOne_time['direction_same'].unique()
```

Out[46]:
```
array([0], dtype=int64)
```

Between at 10AM and 2PM all coupons given were in the opposite direction hence no impact on the outcome for the hours 10AM to 2PM. Then we will focus on the impact of direction for all other groups.

5. Explore impact of direction for all number of visits and all times

In [47]:
```
#Measure Acceptance Numerically for the same direction
df_coffee_Direct = data_coffee.groupby(['CoffeeHouse','direction_same','Coupon_Acceptance'])[['Coupon_Acceptance']].count()
df_coffee_Direct['Coupon_%_Per_Category'] = df_coffee_Direct/df_coffee_Direct.groupby(['CoffeeHouse', 'direction_same']).sum()*100
df_coffee_Direct['Total Acceptance %'] = df_coffee_Direct['Coupon_Acceptance']/df_coffee_Direct['Coupon_Acceptance'].sum()*100
df_coffee_Direct
```

Out[47]:

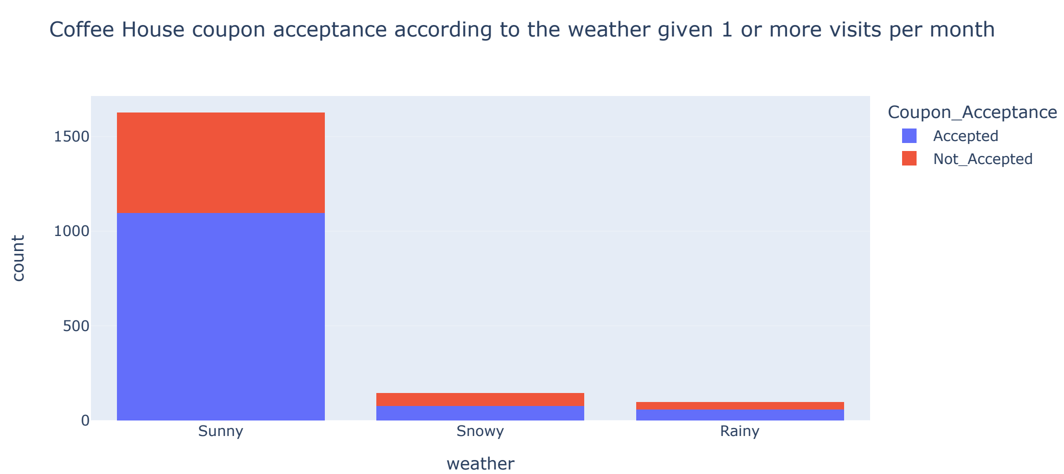
CoffeeHouse	direction_same	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Total Acceptance %
1~3	0	Accepted	543	63.807286	14.229560
		Not_Accepted	308	36.192714	8.071279
	1	Accepted	117	69.642857	3.066038
		Not_Accepted	51	30.357143	1.336478
4~8	0	Accepted	266	65.356265	6.970650
		Not_Accepted	141	34.643735	3.694969
	1	Accepted	80	80.000000	2.096436
		Not_Accepted	20	20.000000	0.524109
gt8	0	Accepted	174	64.444444	4.559748
		Not_Accepted	96	35.555556	2.515723
	1	Accepted	51	70.833333	1.336478
		Not_Accepted	21	29.166667	0.550314
less1	0	Accepted	412	47.962747	10.796646
		Not_Accepted	447	52.037253	11.713836
	1	Accepted	94	48.704663	2.463312
		Not_Accepted	99	51.295337	2.594340
never	0	Accepted	122	17.110799	3.197065
		Not_Accepted	591	82.889201	15.487421
	1	Accepted	35	19.125683	0.917191
		Not_Accepted	148	80.874317	3.878407

Using the direction data, we can see that the impact of same direction is not significant. Hence, same direction or opposite direction does not materially impact in general the groups. But it incrementally increases the chances of acceptance.

6. Explore impact of weather given more than 1 visits per month

In [48]:

```
#We will make a histogram to illustrate the acceptance according to the weather
fig_coffee_weat = px.histogram(data_coffee_MoreOne, x ='weather',color='Coupon_Acceptance',
                         title = 'Coffee House coupon acceptance according to the weather given 1 or more visits per month',
                                width = 900, height = 450)

fig_coffee_weat.show(rendered = 'png')
```



In [49]:

```
#Measure Acceptance Numerically for the weather given more than 1 visit
Tbl_coffe_MoreOne_Weat = data_coffee_MoreOne.groupby(['weather','Coupon_Acceptance'])[['Coupon_Acceptance']].count()
Tbl_coffe_MoreOne_Weat['Coupon_%_Per_Category'] = Tbl_coffe_MoreOne_Weat/Tbl_coffe_MoreOne_Weat.groupby(['weather']).sum()*100
Tbl_coffe_MoreOne_Weat['Total Acceptance %'] = Tbl_coffe_MoreOne_Weat['Coupon_Acceptance']/Tbl_coffe_MoreOne_Weat['Coupon_Acceptance'].sum()*100
Tbl_coffe_MoreOne_Weat
```

Out[49]:

weather	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Total Acceptance %
Rainy	Accepted	57	59.375000	3.051392
	Not_Accepted	39	40.625000	2.087794
Snowy	Accepted	77	53.103448	4.122056
	Not_Accepted	68	46.896552	3.640257
Sunny	Accepted	1097	67.424708	58.725910
	Not_Accepted	530	32.575292	28.372591

In [50]:
```
#Measure Acceptance Numerically for the temperature given more than 1 visit
Tbl_coffe_MoreOne_Temp = data_coffee_MoreOne.groupby(['temperature','Coupon_Acceptance'])[['Coupon_Acceptance']].count()
Tbl_coffe_MoreOne_Temp['Coupon_%_Per_Category'] = Tbl_coffe_MoreOne_Temp/Tbl_coffe_MoreOne_Temp.groupby(['temperature']).sum()*100
Tbl_coffe_MoreOne_Temp['Total Acceptance %'] = Tbl_coffe_MoreOne_Temp['Coupon_Acceptance']/Tbl_coffe_MoreOne_Temp['Coupon_Acceptance'].sum()*100
Tbl_coffe_MoreOne_Temp
```

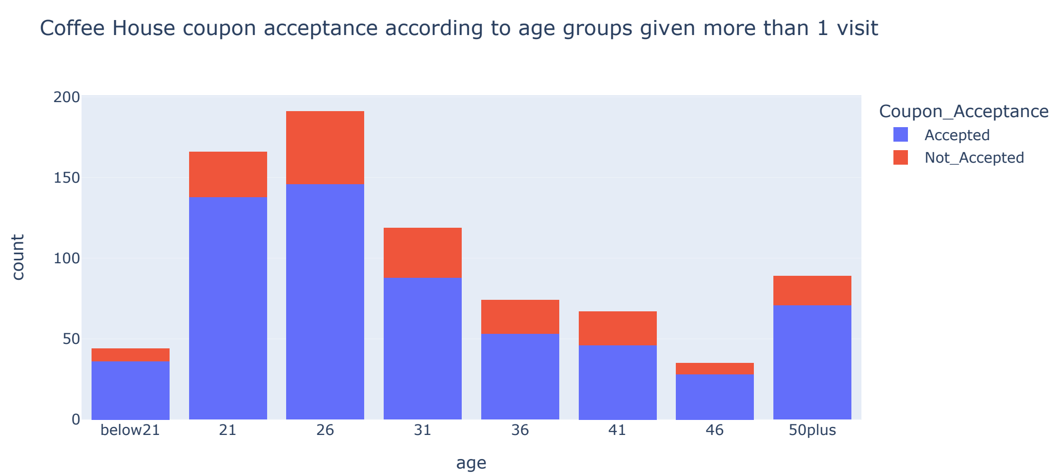
Out[50]:

temperature	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Total Acceptance %
30	Accepted	84	54.545455	4.496788
	Not_Accepted	70	45.454545	3.747323
55	Accepted	358	58.784893	19.164882
	Not_Accepted	251	41.215107	13.436831
80	Accepted	789	71.402715	42.237687
	Not_Accepted	316	28.597285	16.916488

The acceptance of coupons given a warm and sunny day will be higher than other temperature or weather.

7. Explore the acceptance ratio per age group given more than 1 visit and between 10AM and 2PM

In [51]:
```
#Create a histogram to illsutrate the relationship between age and acceptance
fig_coffee_age = px.histogram(data_coffee_MoreOne_time, x ='age',color='Coupon_Acceptance',
                       title = 'Coffee House coupon acceptance according to age groups given more than 1 visit',
                            width = 900, height = 450)
fig_coffee_age.update_xaxes(categoryorder = 'array', categoryarray = ['below21','21', '26', '31', '36', '41', '46', '50plus'])
fig_coffee_age.show(rendered = 'png')
```



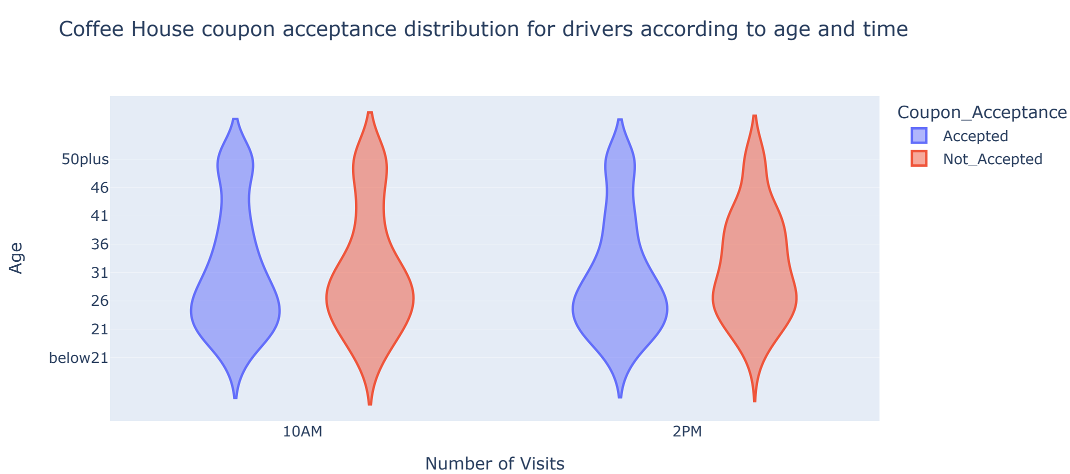
In [52]:
```
#Create a table to illsutrate the relationship between age and acceptance
Tbl_coffe_MoreOne_T_Age = data_coffee_MoreOne_time.groupby(['age','Coupon_Acceptance'])[['Coupon_Acceptance']].count()
Tbl_coffe_MoreOne_T_Age['Coupon_%_Per_Category'] = Tbl_coffe_MoreOne_T_Age/Tbl_coffe_MoreOne_T_Age.groupby(['age']).sum()*100
Tbl_coffe_MoreOne_T_Age['Total Acceptance %'] = Tbl_coffe_MoreOne_T_Age['Coupon_Acceptance']/Tbl_coffe_MoreOne_T_Age['Coupon_Acceptance'].sum()*100
Tbl_coffe_MoreOne_T_Age
```

Out[52]:

age	Coupon_Acceptance	Coupon_Acceptance	Coupon_%_Per_Category	Total Acceptance %
21	Accepted	138	83.132530	17.579618
	Not_Accepted	28	16.867470	3.566879
26	Accepted	146	76.439791	18.598726
	Not_Accepted	45	23.560209	5.732484
31	Accepted	88	73.949580	11.210191
	Not_Accepted	31	26.050420	3.949045
36	Accepted	53	71.621622	6.751592
	Not_Accepted	21	28.378378	2.675159
41	Accepted	46	68.656716	5.859873
	Not_Accepted	21	31.343284	2.675159
46	Accepted	28	80.000000	3.566879
	Not_Accepted	7	20.000000	0.891720
50plus	Accepted	71	79.775281	9.044586
	Not_Accepted	18	20.224719	2.292994
below21	Accepted	36	81.818182	4.585987
	Not_Accepted	8	18.181818	1.019108

The age groups below21 and 21 have the highest chances of accepting coupons between 10AM & 2PM given that they frequently go to a Coffee House.

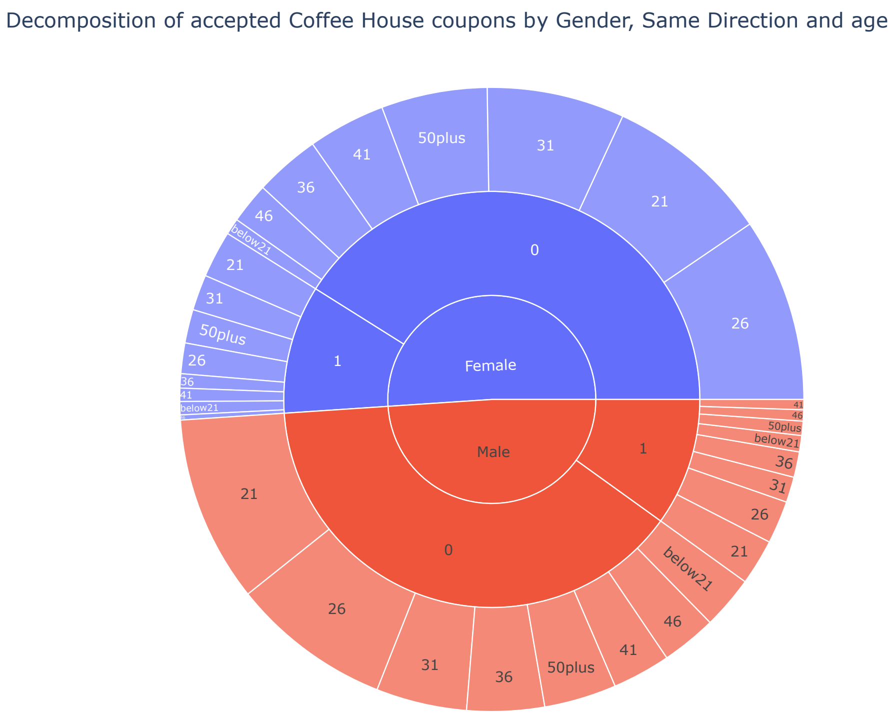
In [53]:
```python
# We will look at the distribution to better understand the sample of age groups
fig_vio_coffee = px.violin(data_coffee_MoreOne_time, x ='time',y='age', color='Coupon_Acceptance',
                           title = 'Coffee House coupon acceptance distribution for drivers according to age and time',
                          width = 900, height = 450)
fig_vio_coffee.update_yaxes(categoryorder = 'array', categoryarray = ['below21','21', '26', '31', '36', '41', '46', '50plus'])
fig_vio_coffee.update_layout(
    xaxis_title='Number of Visits',
    yaxis_title= 'Age')
fig_vio_coffee.show(rendered = 'png')
```



The interesting highlight from the violin graph is that the number of not accepted coupons for the ages 36 and 41 is much thicker at 2PM than for 10AM. This indicates the acceptance rate to be lower for these two groups at 2PM.

8. Given the previous investigation, I want to further understand the breakdown of accepted coupons according the gender, same direction and age variable for all times and number of visits

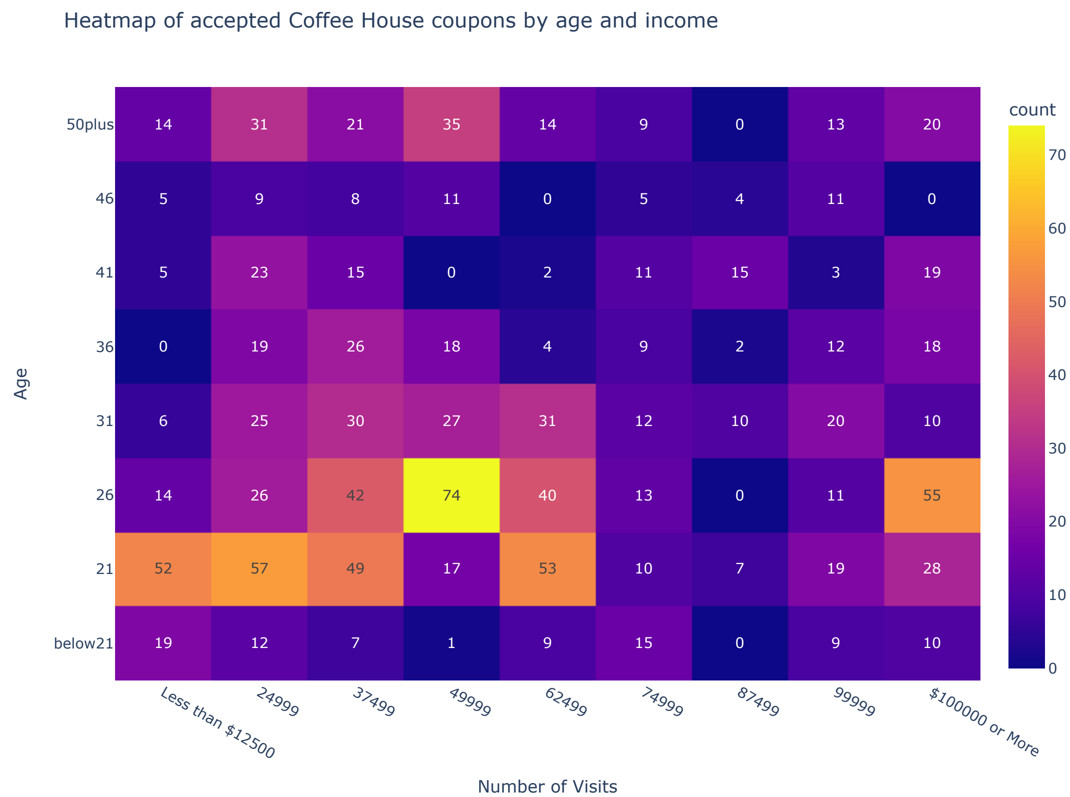
In [54]:
```python
#sunburst chart to better understand the breakdown of the bar dataset
fig_sun_coffee = px.sunburst(data_coffee, path = ['gender','direction_same', 'age'], values='Y',
                             title = 'Decomposition of accepted Coffee House coupons by Gender, Same Direction and age',
                          width = 900, height = 700 )
fig_sun_coffee.show(rendered = 'png')
```



The number of coupons accepted for Coffee House are almost evenly split between male and female. The large majority of coupon accepted were in different direction and were identified by the 0 in the second ring of the sunburst. Furthermore, ages 21 and 26 were the most present in the accepted coupon sample.

9. As a final step, I wanted explore the breakdown of accepted coupons for people visiting a coffee house more than once a month given their age and income.

In [55]:
```
#To do so, we will make a heatmap
fig_heatmap_income = px.density_heatmap(data_coffee_MoreOne.query('Y == 1'), x='income', y='age', text_auto = True,
                                       title = 'Heatmap of accepted Coffee House coupons by age and income',
                                         width = 900, height = 700 )


fig_heatmap_income.update_yaxes(categoryorder = 'array', categoryarray = ['below21','21', '26', '31', '36', '41', '46', '50plus'])
fig_heatmap_income.update_xaxes(categoryorder = 'array', categoryarray = ['Less than $12500','$12500 - $24999',
                                                    '$25000 - $37499', '$37500 - $49999','$50000 - $62499', '$62500 - $74999',
                                                                                '$75000 - $87499','$87500 - $99999','$100000 or More'])
fig_heatmap_income.update_layout(
    xaxis_title='Number of Visits',
    yaxis_title= 'Age')

fig_heatmap_income.show(rendered = 'png')
```



We can notice the heatmap highlights that most acceptance are lower income and ages of 26-21. The age of 21 seems to be the most likely to accept coupons. Looking back at our violin plot, the heatmap may not be as significant since the sample containe a larger sample of this age group translating in a higher presence in the heatmap. On the other hand, there seems to be a correlation for lower end income to accept more coffee house coupons.

Investigation Conclusion

Given the following observations:

1. The more the visits the higher the acceptance of coupons.
2. The highest acceptance times are 10AM and 2PM.
3. A small increase in acceptance of coupons is present for people going in the same direction as the coupon.
4. When it is 80 and when it is sunny, there is a higher chance to accept coffee house coupons.
5. People with a salary of 12500-62499 had the most coupons accepted.
6. The ages of below21 and 21 had the highest acceptance ratio of all age groups.

We can hypothesize the following:

- The more the visits per month the higher the acceptance of coupons.
- Between time of 10AM and 2PM, coupons have a much higher chance of being accepted.
- Offering coupons on a hot sunny day has a higher chance of being accepted.
- Coupons will be more accepted by people with salary of 12500-62499

Practical Application Conclusion

Accros both our investigation and the bar questions, we were able to see that the frequency of visits greatly impact the acceptance rate. In general, the more often a person visited a eatery, the more likely he was to accept to coupon. When it is hot, both coupons saw an increase in acceptance. The age group for both coupon, showed to be an important variable impacting the acceptance rate. In bars, ages of 25 or more had a better chance to accept coupons. In addition, when visiting a bar regularly, having a passanger other than a kid made the acceptance ratio much higher. Coffee House saw a significant increase in acceptance given the time of day with 10AM and 2PM having the highest acceptance ratio.

Future Recommendation

- Since data was all categorical or boolean, we could not use powerful tools such as scatter plots or pair plots. Collecting such data such as salary or geographical location could be very useful.
- The sample of data varying greatly between groups made the interpretation challenging at a higher level. For instance, the sunburst chart indicated that opposite direction was most present in the accepted coupons but when making subgroups, we were able to conclude that the same direction had a higher chance of being accepted. Future exploration could focus on addressing such problem.
- We can explore the impact of attending various types of coupons.
- Explore more coupon types although the commonality were highlighted across two coupons types, it would be interesting to explore more coupons and the commonality across these groups.
- Explore interaction between the variable columns.

- Explore if earning higher salary impacts the exclusivity of spending/the chance of accepting coupons at more than one type of restaurant/eatery.

In [ ]:

```

```

In [ ]:

```

```