

ks-customer-behaviour-segmentation

March 7, 2024

```
[1]: import numpy as np
import pandas as pd
```

Problem Statement Understand the characteristics of customer that will continue buying products

Problem Solution

- Analyse and understand the behavioural aspects of Starbucks customer
- Perform customer segmentation based on the study
- Find out key parameters of the customer loyalty using Chi-Square test of independence

```
[5]: import matplotlib.pyplot as plt
from matplotlib.patches import Patch
import seaborn as sns
import scipy.stats as st
import warnings
warnings.filterwarnings('ignore')
```

```
[29]: df = pd.read_csv("Starbucks satisfactory survey.csv")
df.head()
```

```
[29]:
```

	Timestamp	1. Your Gender	2. Your Age \
0	2019/10/01 12:38:43 PM GMT+8	Female	From 20 to 29
1	2019/10/01 12:38:54 PM GMT+8	Female	From 20 to 29
2	2019/10/01 12:38:56 PM GMT+8	Male	From 20 to 29
3	2019/10/01 12:39:08 PM GMT+8	Female	From 20 to 29
4	2019/10/01 12:39:20 PM GMT+8	Male	From 20 to 29

	3. Are you currently...?	4. What is your annual income? \
0	Student	Less than RM25,000
1	Student	Less than RM25,000
2	Employed	Less than RM25,000
3	Student	Less than RM25,000
4	Student	Less than RM25,000

	5. How often do you visit Starbucks?	6. How do you usually enjoy Starbucks? \
0	Rarely	Dine in

1	Rarely	Take away
2	Monthly	Dine in
3	Rarely	Take away
4	Monthly	Take away

7. How much time do you normally spend during your visit? \

0	Between 30 minutes to 1 hour
1	Below 30 minutes
2	Between 30 minutes to 1 hour
3	Below 30 minutes
4	Between 30 minutes to 1 hour

8. The nearest Starbucks's outlet to you is...? \

0	within 1km
1	1km - 3km
2	more than 3km
3	more than 3km
4	1km - 3km

9. Do you have Starbucks membership card? ... \

0	Yes ...
1	Yes ...
2	Yes ...
3	No ...
4	No ...

11. On average, how much would you spend at Starbucks per visit? \

0	Less than RM20
1	Less than RM20
2	Less than RM20
3	Less than RM20
4	Around RM20 - RM40

12. How would you rate the quality of Starbucks compared to other brands (Coffee Bean, Old Town White Coffee..) to be: \

0	4
1	4
2	4
3	2
4	3

13. How would you rate the price range at Starbucks? \

0	3
1	3
2	3
3	1
4	3

14. How important are sales and promotions in your purchase decision? \

0	5
1	4
2	4
3	4
4	4

15. How would you rate the ambiance at Starbucks? (lighting, music, etc...)

\	
0	5
1	4
2	4
3	3
4	2

16. You rate the WiFi quality at Starbucks as.. \

0	4
1	4
2	4
3	3
4	2

17. How would you rate the service at Starbucks? (Promptness, friendliness, etc..) \

0	4
1	5
2	4
3	3
4	3

18. How likely you will choose Starbucks for doing business meetings or hangout with friends? \

0	3
1	2
2	3
3	3
4	3

19. How do you come to hear of promotions at Starbucks? Check all that apply.

\	
0	Starbucks Website/Apps;Social Media;Emails;Dea...
1	Social Media;In Store displays
2	In Store displays;Billboards
3	Through friends and word of mouth
4	Starbucks Website/Apps;Social Media

```

20. Will you continue buying at Starbucks?
0                                     Yes
1                                     Yes
2                                     Yes
3                                     No
4                                     Yes

```

[5 rows x 21 columns]

0.0.1 Data Wrangling

```

[33]: df.columns = ['Timestamp',
                    'Gender',
                    'Age',
                    'Occupation',
                    'Annual_Income',
                    'Visit_Frequency',
                    'Service_preferred',
                    'Time_Spent_Frequency',
                    'Nearest_Store_Distance',
                    'Membership',
                    'Frequent_Product',
                    'Avg_Money_Spent',
                    'Quality_Rating_vs_Other_Brands',
                    'Price_Rating',
                    'Sales_Promotion_Importance',
                    'Ambiance_Rating',
                    'WiFi_Rating',
                    'Service_Rating',
                    'Meetings_hangouts_preference',
                    'Promotion_Source',
                    'Loyalty'
                    ]

df.head()

```

```

[33]:
      Timestamp  Gender  Age  Occupation \
0  2019/10/01 12:38:43 PM GMT+8  Female  From 20 to 29  Student
1  2019/10/01 12:38:54 PM GMT+8  Female  From 20 to 29  Student
2  2019/10/01 12:38:56 PM GMT+8   Male  From 20 to 29  Employed
3  2019/10/01 12:39:08 PM GMT+8  Female  From 20 to 29  Student
4  2019/10/01 12:39:20 PM GMT+8   Male  From 20 to 29  Student

      Annual_Income  Visit_Frequency  Service_preferred \
0  Less than RM25,000      Rarely      Dine in
1  Less than RM25,000      Rarely      Take away
2  Less than RM25,000     Monthly      Dine in
3  Less than RM25,000      Rarely      Take away

```

4	Less than RM25,000	Monthly	Take away		
---	--------------------	---------	-----------	--	--

	Time_Spent_Frequency	Nearest_Store_Distance	Membership	...	\
0	Between 30 minutes to 1 hour	within 1km	Yes	...	
1	Below 30 minutes	1km - 3km	Yes	...	
2	Between 30 minutes to 1 hour	more than 3km	Yes	...	
3	Below 30 minutes	more than 3km	No	...	
4	Between 30 minutes to 1 hour	1km - 3km	No	...	

	Avg_Money_Spent	Quality_Rating_vs_Other_Brands	Price_Rating	\
0	Less than RM20	4	3	
1	Less than RM20	4	3	
2	Less than RM20	4	3	
3	Less than RM20	2	1	
4	Around RM20 - RM40	3	3	

	Sales_Promotion_Importance	Ambiance_Rating	WiFi_Rating	Service_Rating	\
0	5	5	4	4	
1	4	4	4	5	
2	4	4	4	4	
3	4	3	3	3	
4	4	2	2	3	

	Meetings_hangouts_preference	\
0	3	
1	2	
2	3	
3	3	
4	3	

	Promotion_Source	Loyalty
0	Starbucks Website/Apps;Social Media;Emails;Dea...	Yes
1	Social Media;In Store displays	Yes
2	In Store displays;Billboards	Yes
3	Through friends and word of mouth	No
4	Starbucks Website/Apps;Social Media	Yes

[5 rows x 21 columns]

```
[8]: len(df)
```

```
[8]: 122
```

Check the different Columns datatypes and null values

```
[34]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

RangeIndex: 122 entries, 0 to 121

Data columns (total 21 columns):

#	Column	Non-Null Count	Dtype
0	Timestamp	122 non-null	object
1	Gender	122 non-null	object
2	Age	122 non-null	object
3	Occupation	122 non-null	object
4	Annual_Income	122 non-null	object
5	Visit_Frequency	122 non-null	object
6	Service_preferred	121 non-null	object
7	Time_Spent_Frequency	122 non-null	object
8	Nearest_Store_Distance	122 non-null	object
9	Membership	122 non-null	object
10	Frequent_Product	122 non-null	object
11	Avg_Money_Spent	122 non-null	object
12	Quality_Rating_vs_Other_Brands	122 non-null	int64
13	Price_Rating	122 non-null	int64
14	Sales_Promotion_Importance	122 non-null	int64
15	Ambiance_Rating	122 non-null	int64
16	WiFi_Rating	122 non-null	int64
17	Service_Rating	122 non-null	int64
18	Meetings_hangouts_preference	122 non-null	int64
19	Promotion_Source	121 non-null	object
20	Loyalty	122 non-null	object

dtypes: int64(7), object(14)

memory usage: 20.1+ KB

```
[35]: df[df.Service_preferred.isnull()]
```

```
[35]:
```

	Timestamp	Gender	Age	Occupation	
81	2019/10/03 9:11:28 AM GMT+8	Male	From 20 to 29	Employed	
	Annual_Income	Visit_Frequency	Service_preferred	Time_Spent_Frequency	
81	Less than RM25,000	Never	NaN	Below 30 minutes	
	Nearest_Store_Distance	Membership	...	Avg_Money_Spent	
81	more than 3km	No	...	Zero	
	Quality_Rating_vs_Other_Brands	Price_Rating	Sales_Promotion_Importance		
81		1	1		1
	Ambiance_Rating	WiFi_Rating	Service_Rating		
81	3	3	3		
	Meetings_hangouts_preference	Promotion_Source	Loyalty		
81		3	NaN	No	

[1 rows x 21 columns]

```
[36]: # Only one row has null value. Delete the row
df = df[-df.Service_preferred.isnull()]
len(df)
```

[36]: 121

```
[37]: df.describe()
```

```
[37]:
```

	Quality_Rating_vs_Other_Brands	Price_Rating	\
count	121.000000	121.000000	
mean	3.685950	2.909091	
std	0.913173	1.072381	
min	1.000000	1.000000	
25%	3.000000	2.000000	
50%	4.000000	3.000000	
75%	4.000000	4.000000	
max	5.000000	5.000000	

	Sales_Promotion_Importance	Ambiance_Rating	WiFi_Rating	\
count	121.000000	121.000000	121.000000	
mean	3.818182	3.760331	3.256198	
std	1.064581	0.931171	0.962020	
min	1.000000	1.000000	1.000000	
25%	3.000000	3.000000	3.000000	
50%	4.000000	4.000000	3.000000	
75%	5.000000	4.000000	4.000000	
max	5.000000	5.000000	5.000000	

	Service_Rating	Meetings_hangouts_preference
count	121.000000	121.000000
mean	3.752066	3.520661
std	0.829468	1.033595
min	1.000000	1.000000
25%	3.000000	3.000000
50%	4.000000	4.000000
75%	4.000000	4.000000
max	5.000000	5.000000

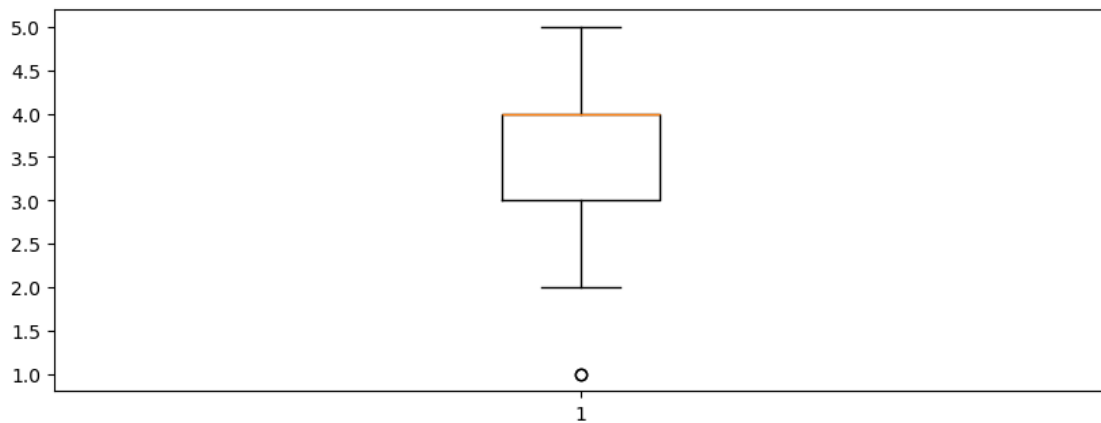
Univariate Analysis

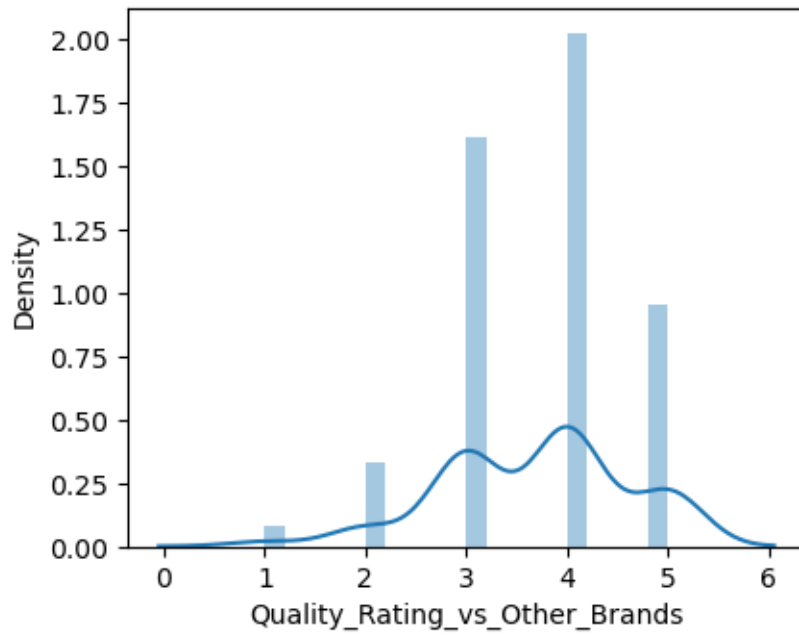
```
[38]: num_cols = df.select_dtypes(include='int64').columns
num_cols
```

```
[38]: Index(['Quality_Rating_vs_Other_Brands', 'Price_Rating',  
          'Sales_Promotion_Importance', 'Ambiance_Rating', 'WiFi_Rating',  
          'Service_Rating', 'Meetings_hangouts_preference'],  
          dtype='object')
```

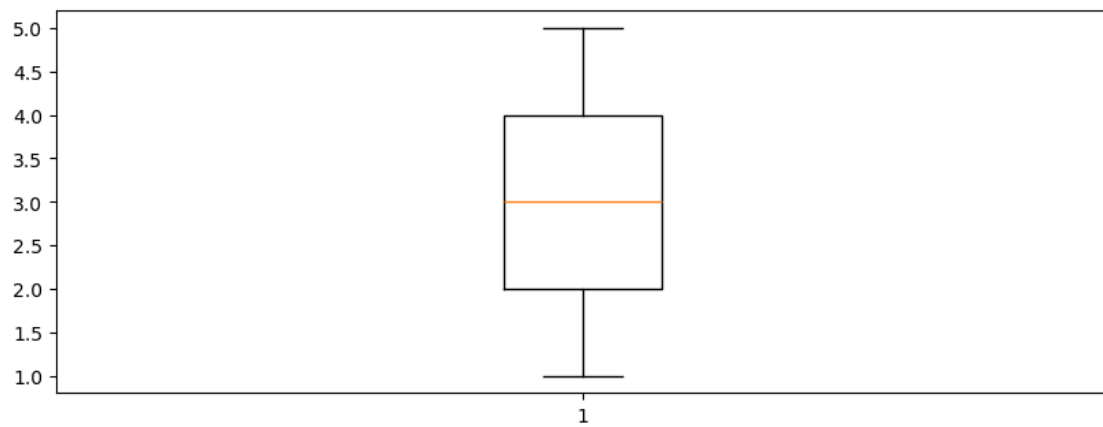
```
[21]: def plot_numeric(df,x):  
    plt.figure(figsize=(10,8))  
    plt.subplot(2,1,1)  
    plt.boxplot(df[i], vert=True)  
    plt.show()  
    plt.figure(figsize=(10,8))  
    plt.subplot(2,2,2)  
    sns.distplot(df[i], bins=20)  
    plt.show()  
  
for i in num_cols:  
    print("Plots for Column: "+ i)  
    plot_numeric(df,i)  
    print("\n")
```

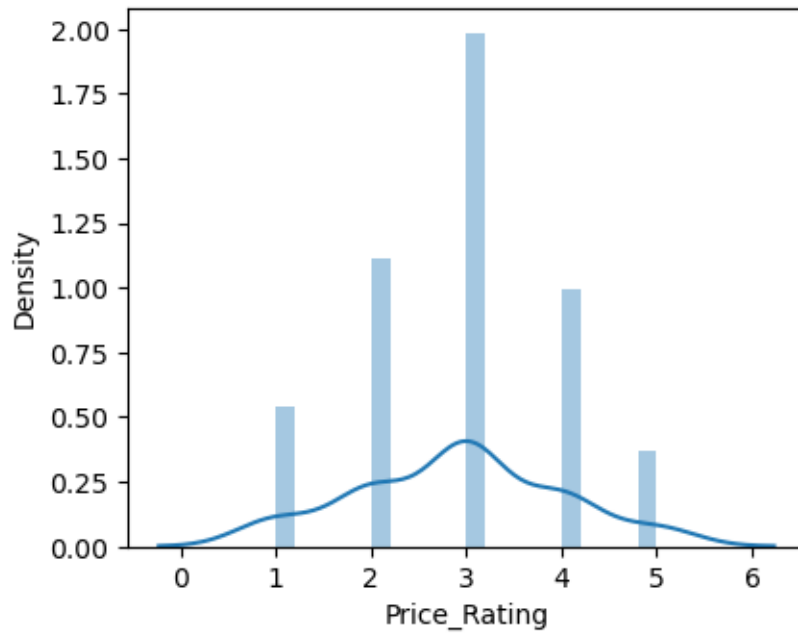
Plots for Column: Quality_Rating_vs_Other_Brands



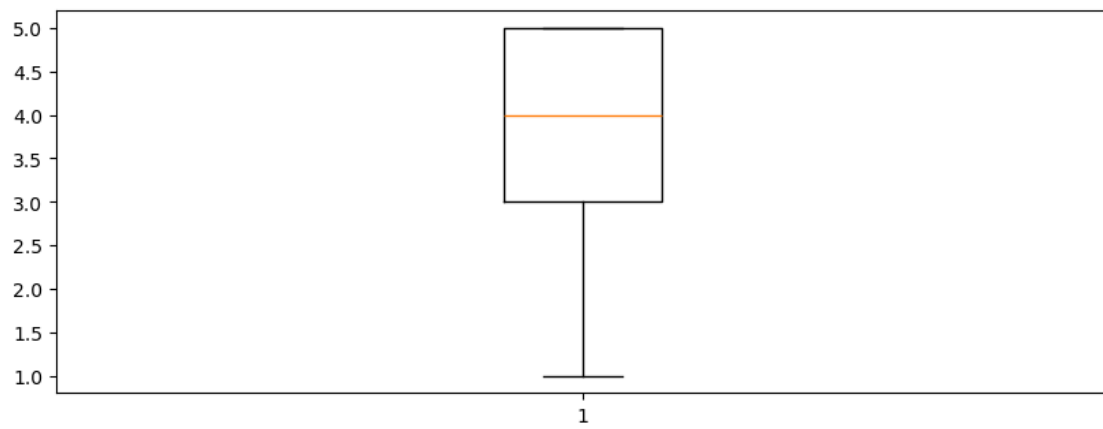


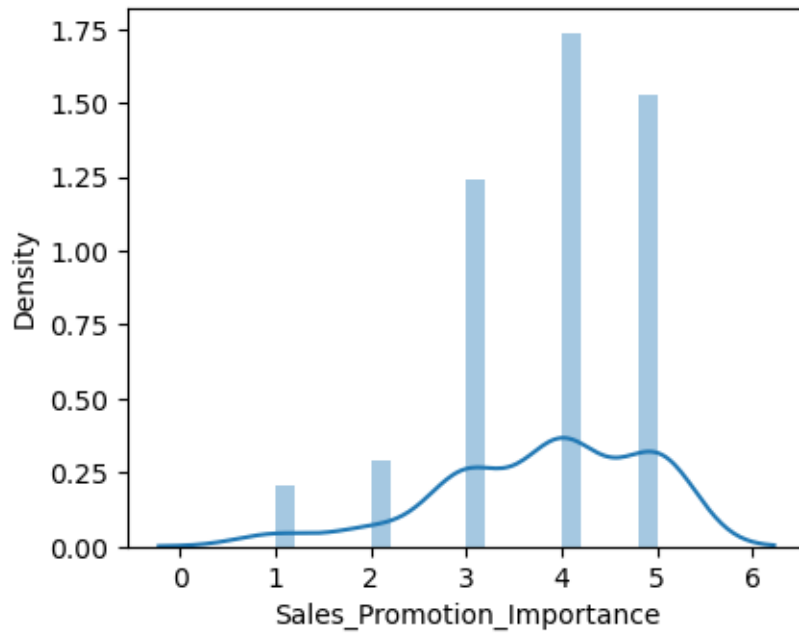
Plots for Column: Price_Rating



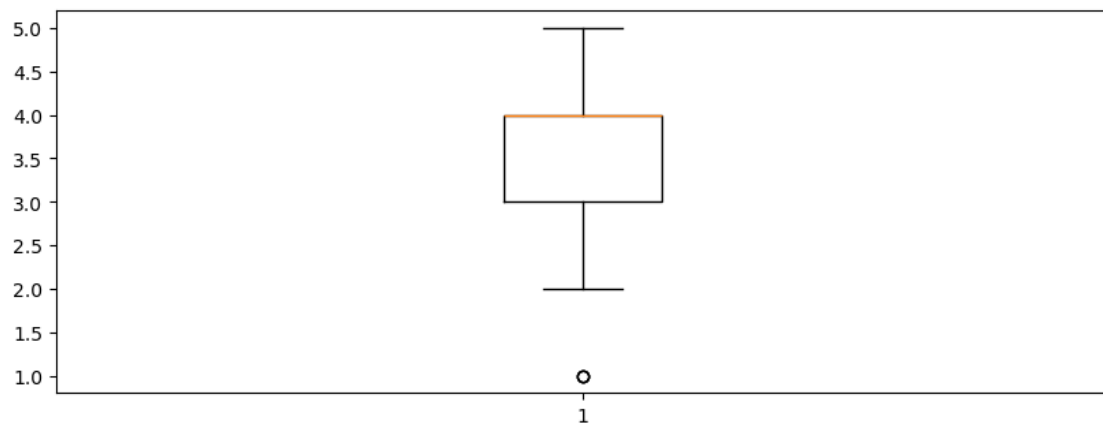


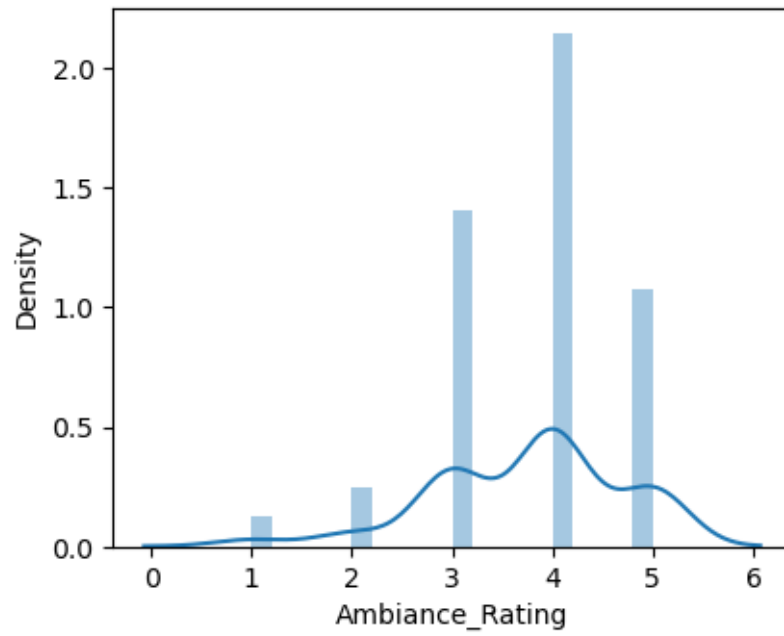
Plots for Column: Sales_Promotion_Importance



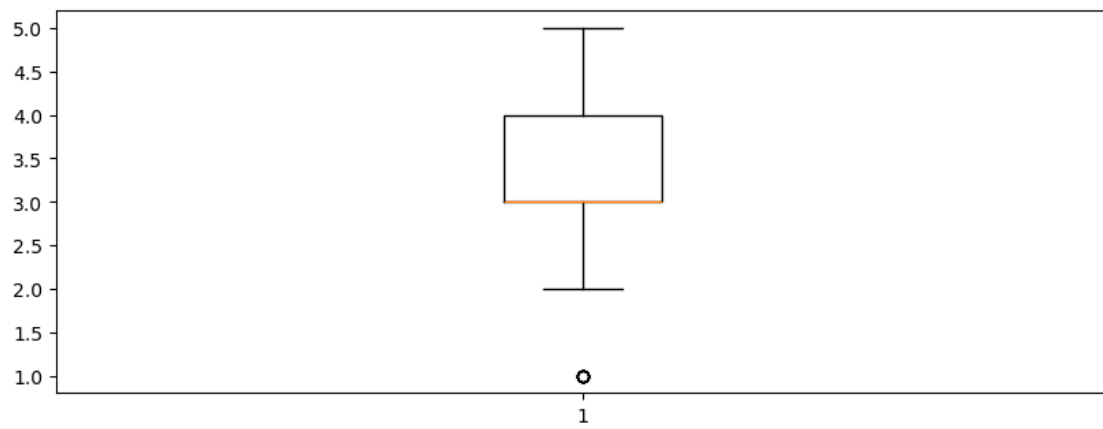


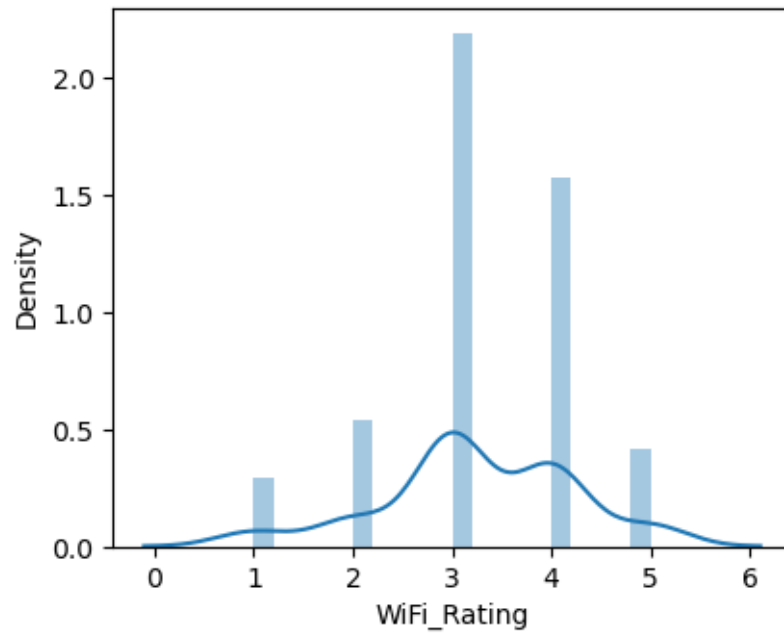
Plots for Column: Ambiance_Rating



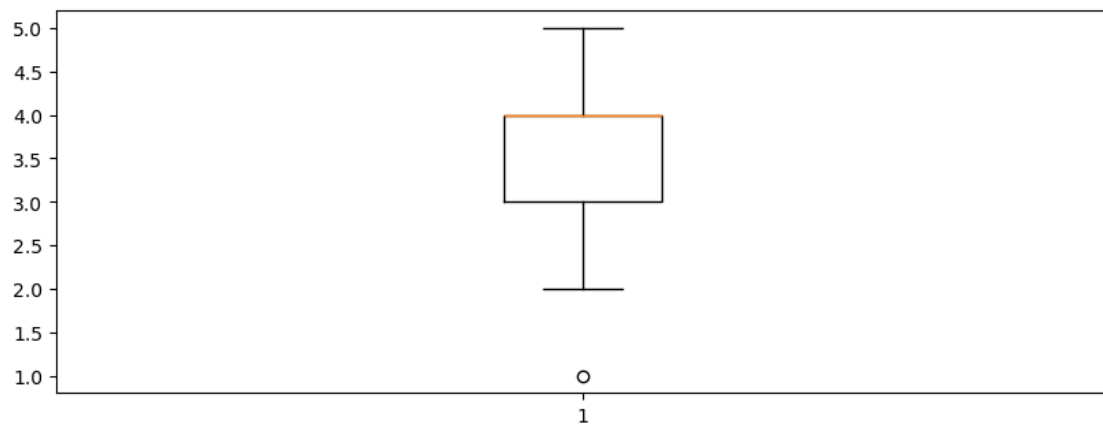


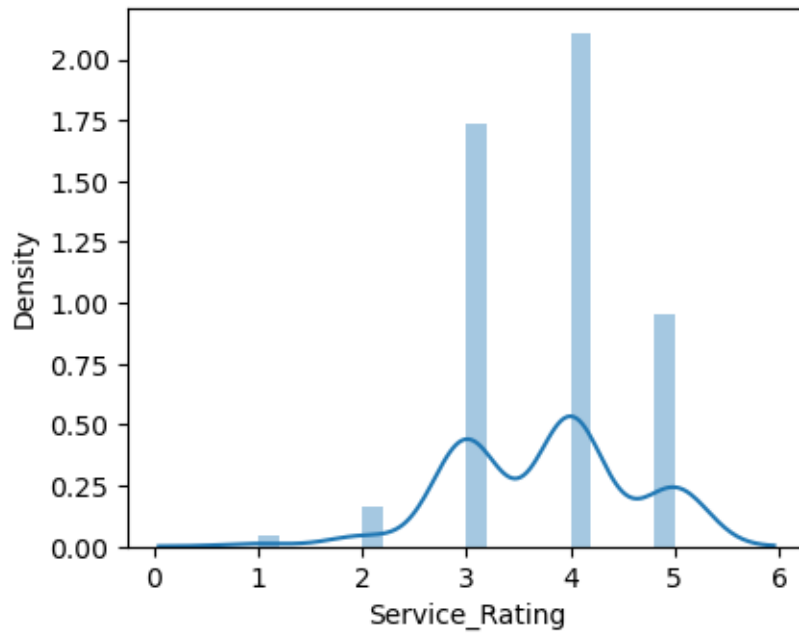
Plots for Column: WiFi_Rating



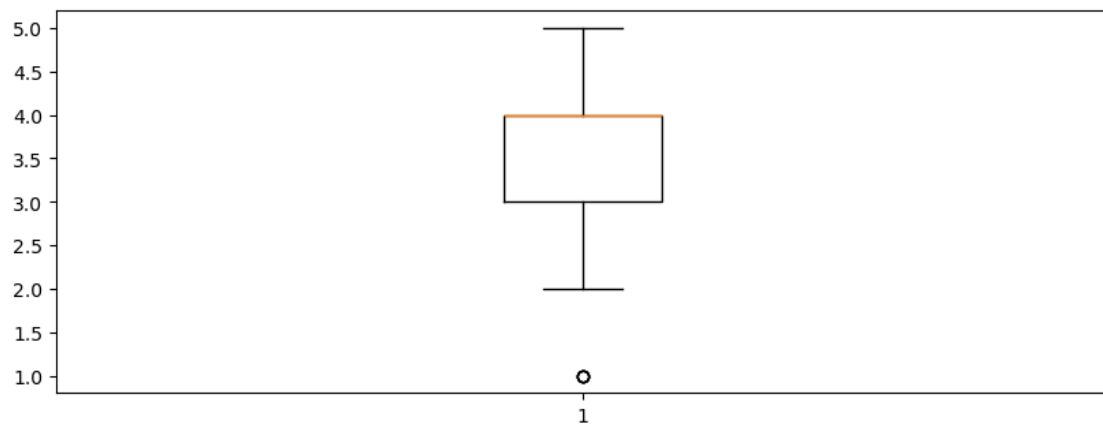


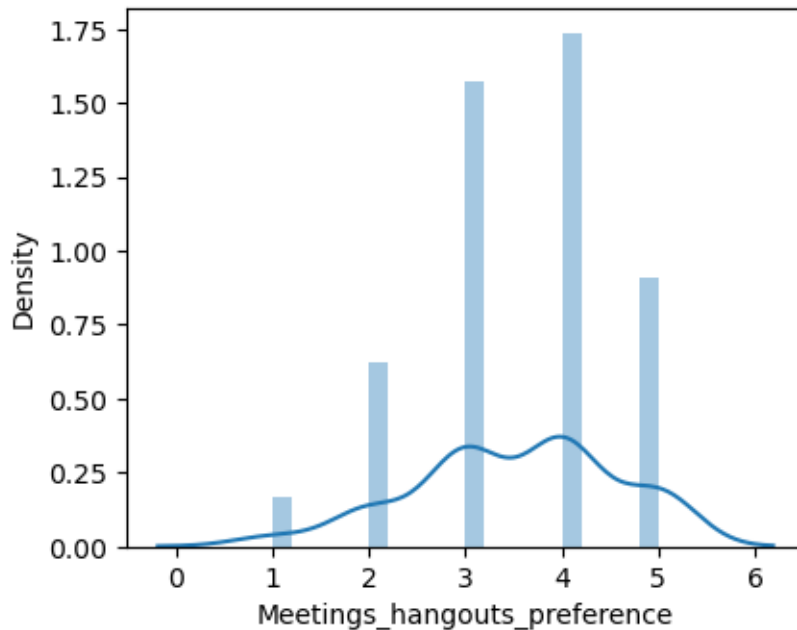
Plots for Column: Service_Rating





Plots for Column: Meetings_hangouts_preference





- Majority customers(50%) rated 4 for quality vs other brands
- Price rating is uniformly distributed. There are approximately equal no of customers who can afford or not afford the prices
- Sales and Promotion have very good impact on the customer purchase decision(90% cusomters rated above 3)
- Majority customers rated ambiance ≥ 3 (90%)
- Majority customers rated wifi service 3 (around 55%)
- The Serivce ratings given by the customers are around 3-5(around 90% customers)
- around 80% customers prefer Starbucks for Meetings/hangouts

From the above graphs we can see there are outliers in the data. Lets check the dataset

```
[39]: df[df.Quality_Rating_vs_Other_Brands <2]
```

```
[39]:
```

	Timestamp	Gender	Age	Occupation	\
112	2019/10/03 7:58:17 PM GMT+8	Male	From 20 to 29	Student	
121	2019/10/05 4:57:22 PM GMT+8	Male	From 20 to 29	Employed	

	Annual_Income	Visit_Frequency	Service_preferred	\
112	More than RM150,000	Never	Never	
121	RM50,000 - RM100,000	Rarely	Dine in	

	Time_Spent_Frequency	Nearest_Store_Distance	Membership	...	\
--	----------------------	------------------------	------------	-----	---

112	Below 30 minutes	more than 3km	No	...
121	Between 30 minutes to 1 hour	1km - 3km	No	...

	Avg_Money_Spent	Quality_Rating_vs_Other_Brands	Price_Rating	\
112	Zero	1	1	
121	Less than RM20	1	1	

	Sales_Promotion_Importance	Ambiance_Rating	WiFi_Rating	Service_Rating	\
112	1	1	1	1	
121	5	4	3	3	

	Meetings_hangouts_preference	Promotion_Source	Loyalty
112	1	Billboards	No
121	2	In Store displays	No

[2 rows x 21 columns]

```
[40]: df = df[df.Quality_Rating_vs_Other_Brands > 1]
len(df)
```

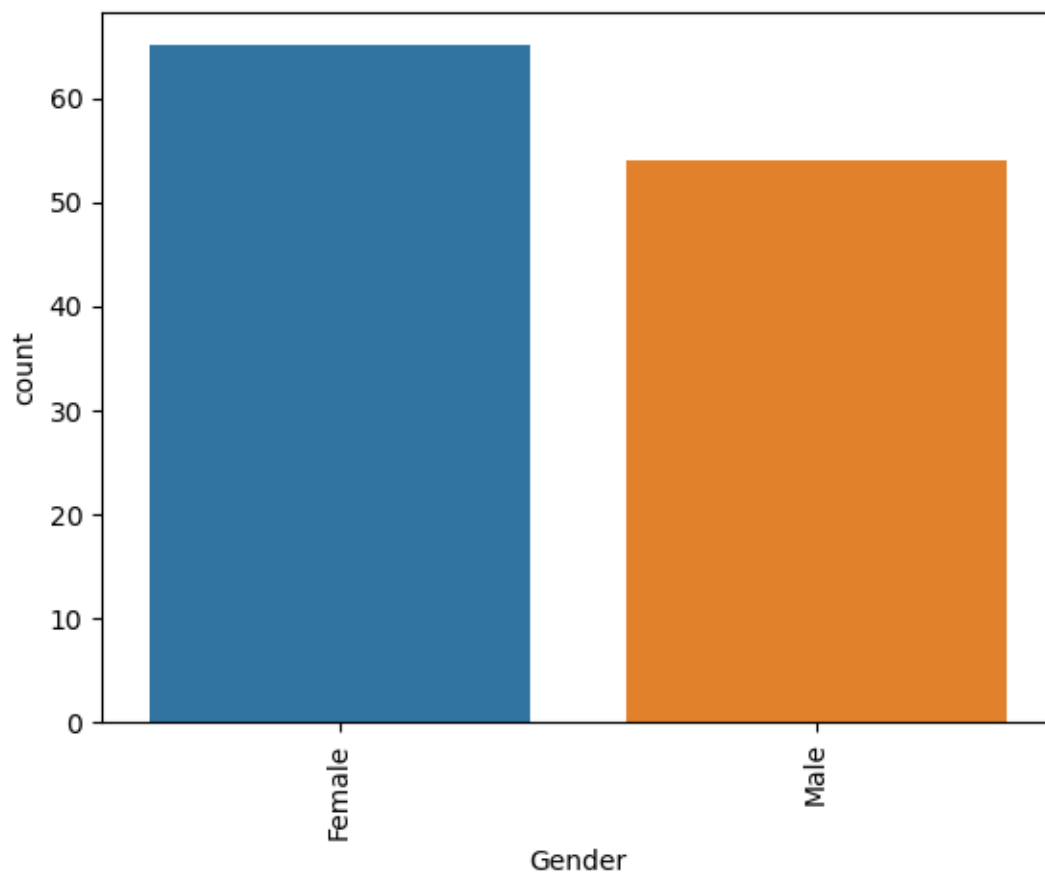
[40]: 119

```
[41]: cat_cols = df.select_dtypes(include='object').columns
cat_cols
```

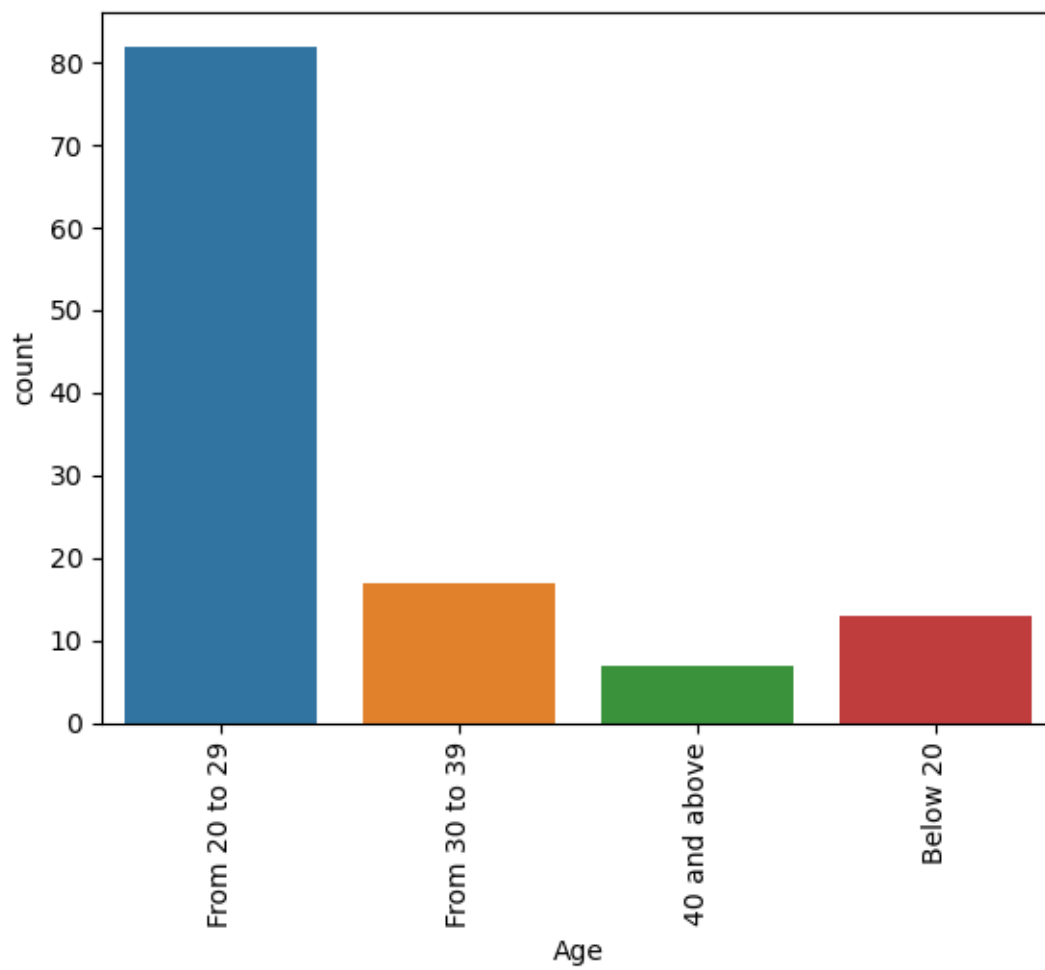
```
[41]: Index(['Timestamp', 'Gender', 'Age', 'Occupation', 'Annual_Income',
          'Visit_Frequency', 'Service_preferred', 'Time_Spent_Frequency',
          'Nearest_Store_Distance', 'Membership', 'Frequent_Product',
          'Avg_Money_Spent', 'Promotion_Source', 'Loyalty'],
          dtype='object')
```

```
[48]: for i in cat_cols[1:]:
        print("CountPlot for the column: "+ i)
        sns.countplot(x=df[i], data=df)
        plt.xticks(rotation=90)
        plt.show()
```

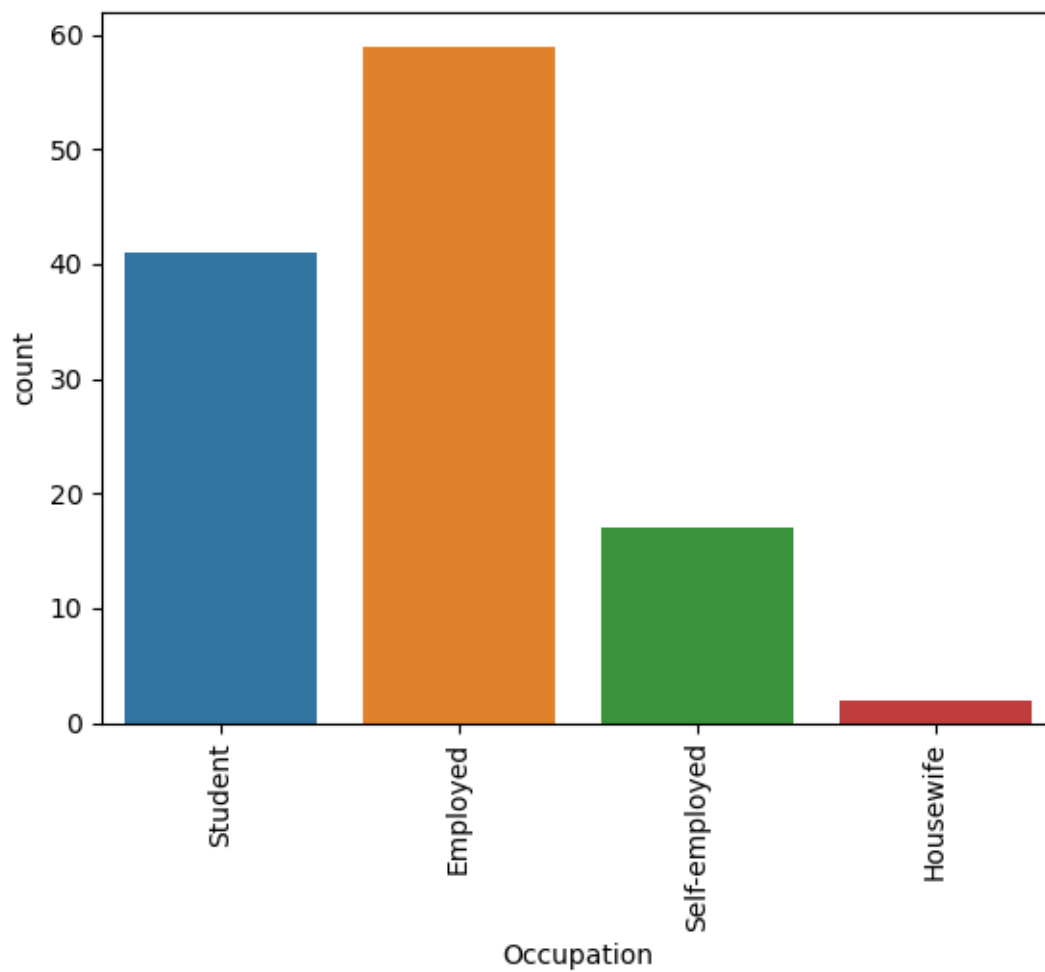
CountPlot for the column: Gender



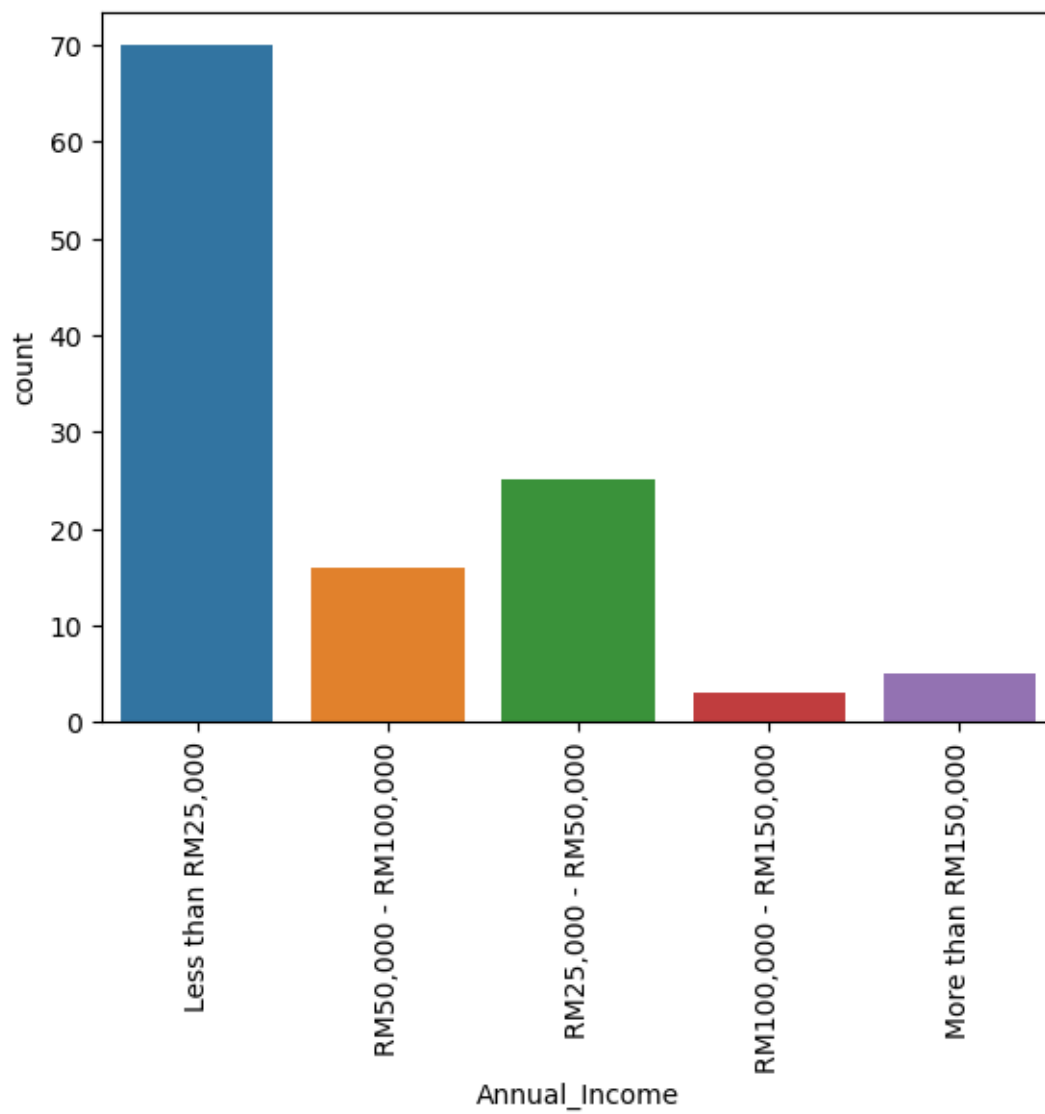
CountPlot for the column: Age



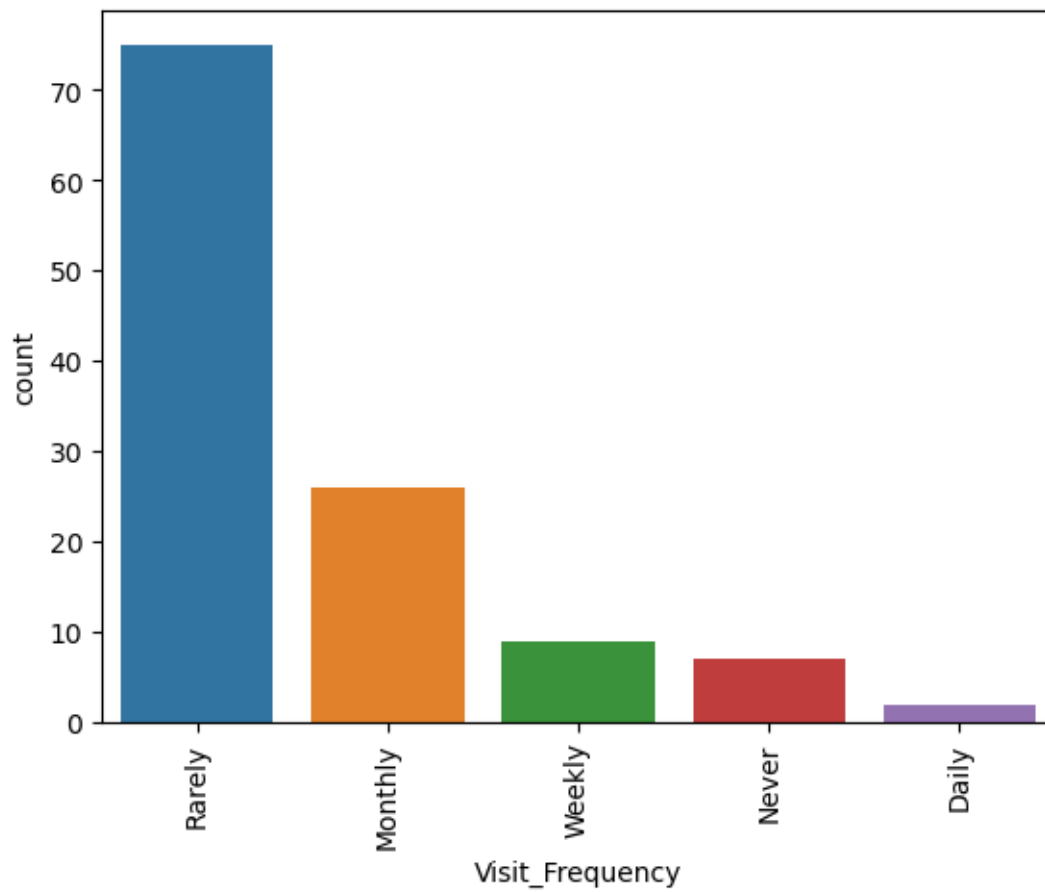
CountPlot for the column: Occupation



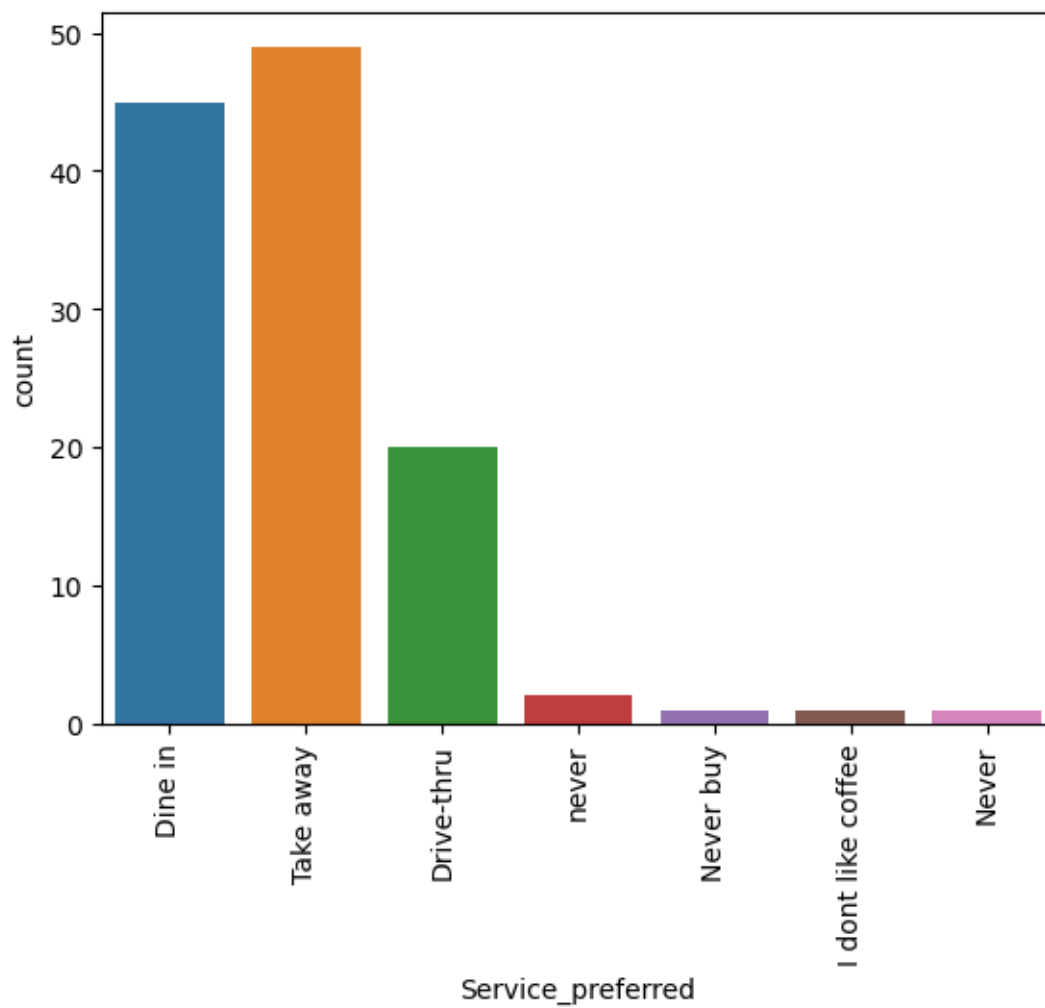
CountPlot for the column: Annual_Income



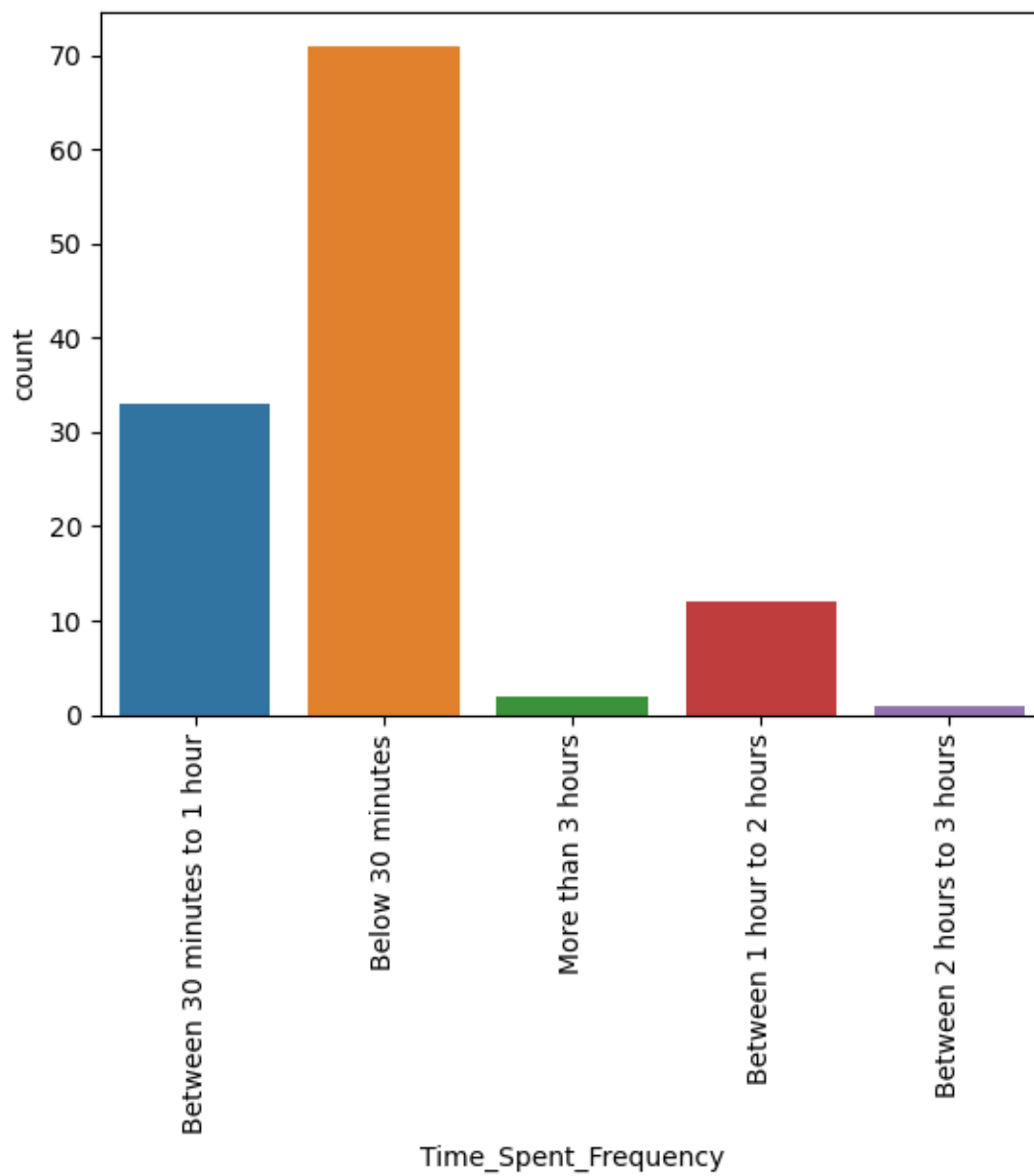
CountPlot for the column: Visit_Frequency



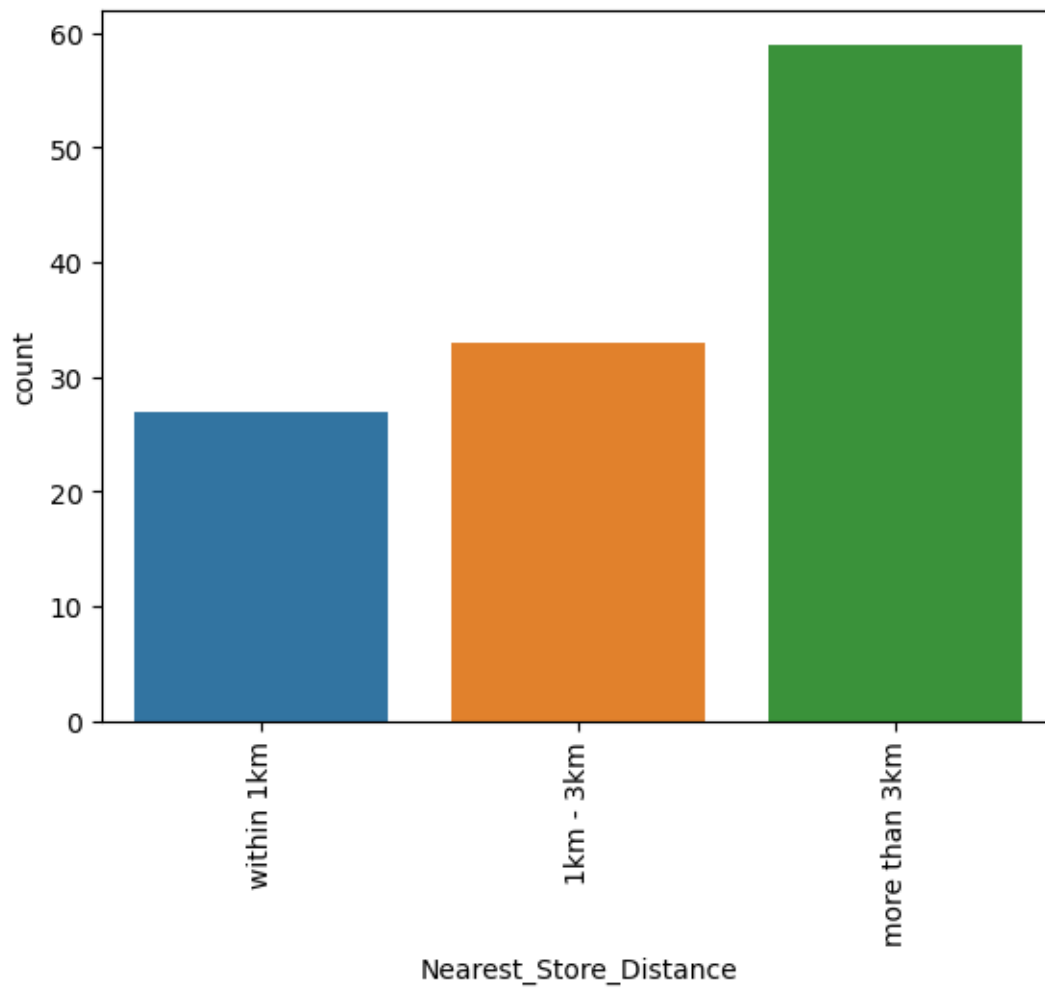
CountPlot for the column: Service_preferred



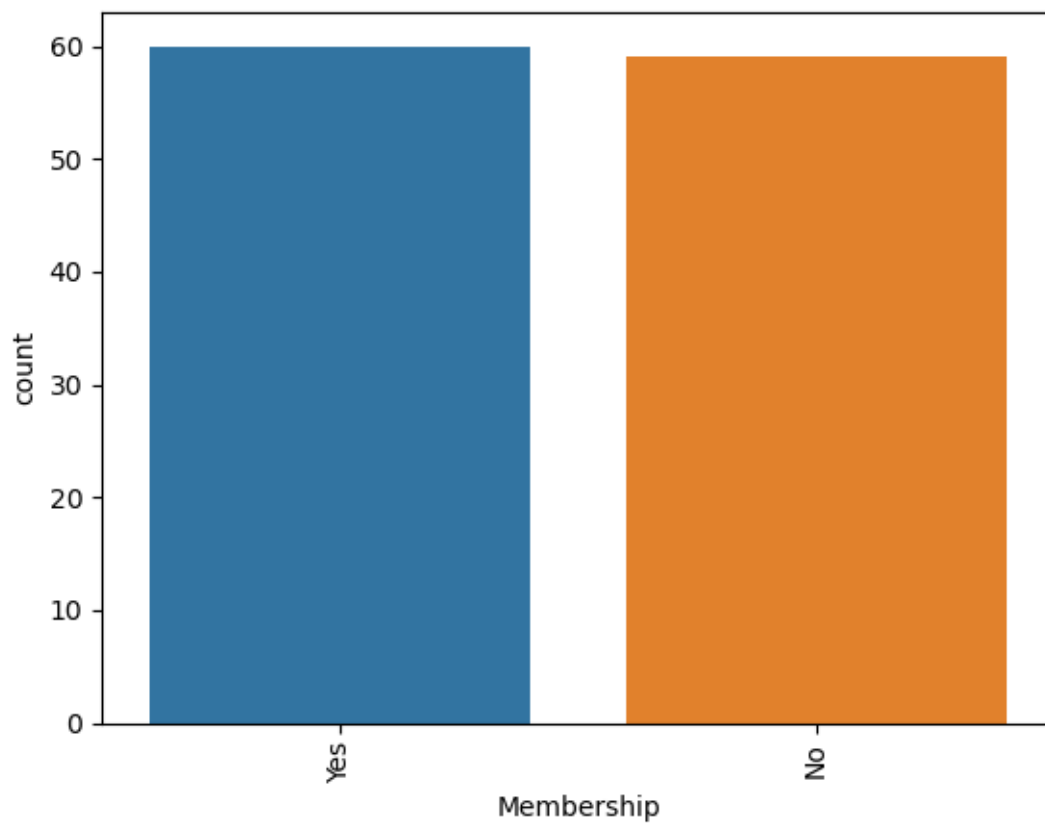
CountPlot for the column: Time_Spent_Frequency



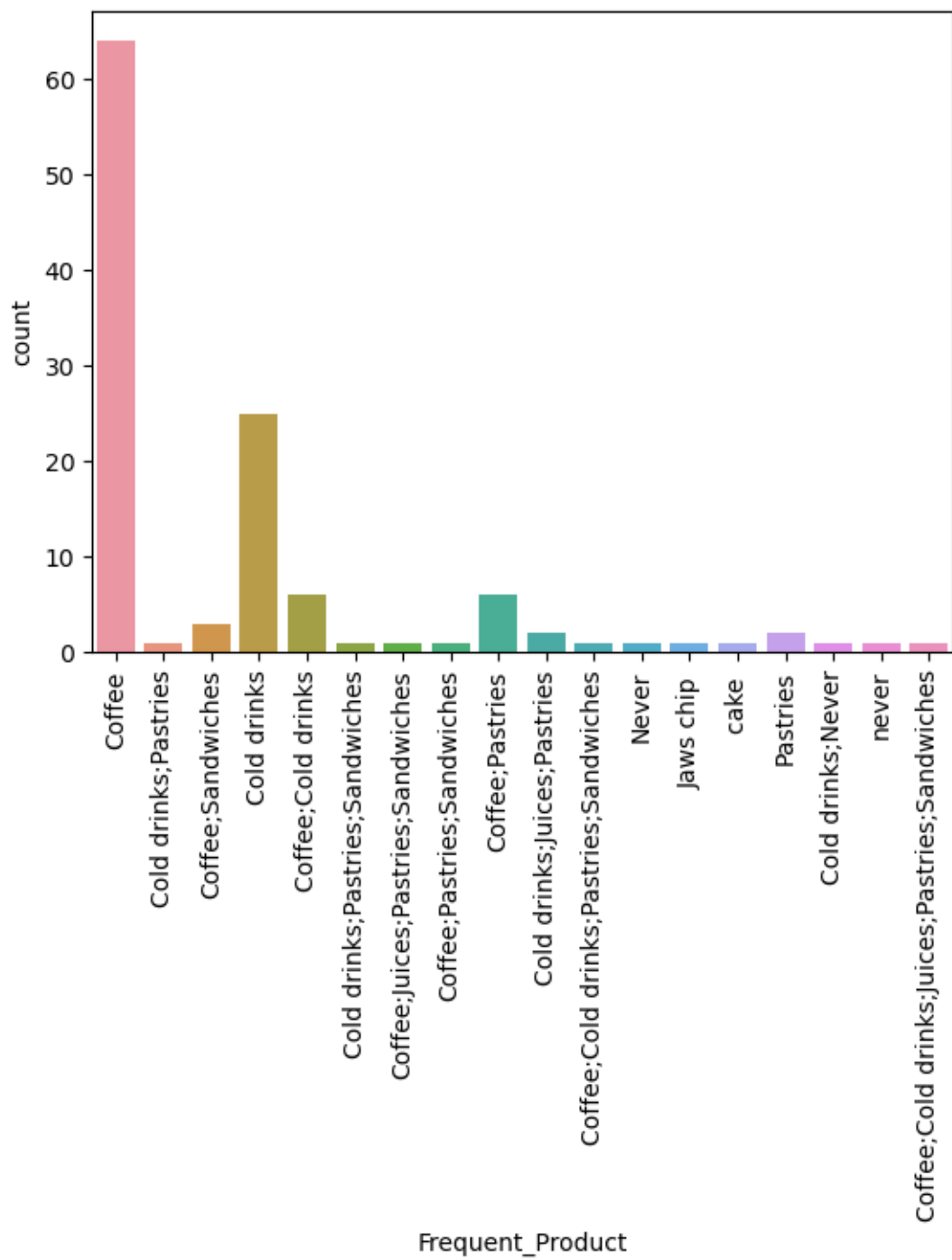
CountPlot for the column: Nearest_Store_Distance



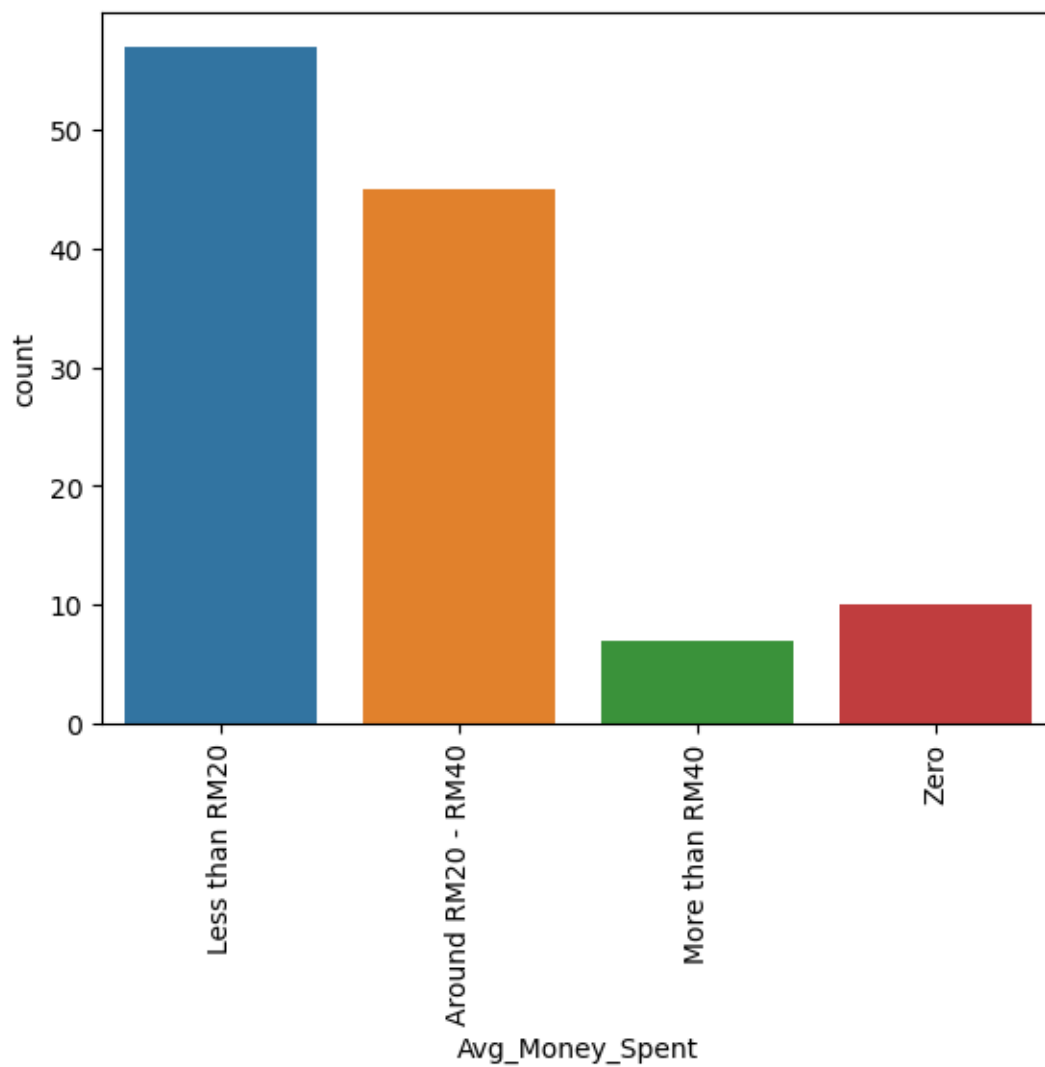
CountPlot for the column: Membership



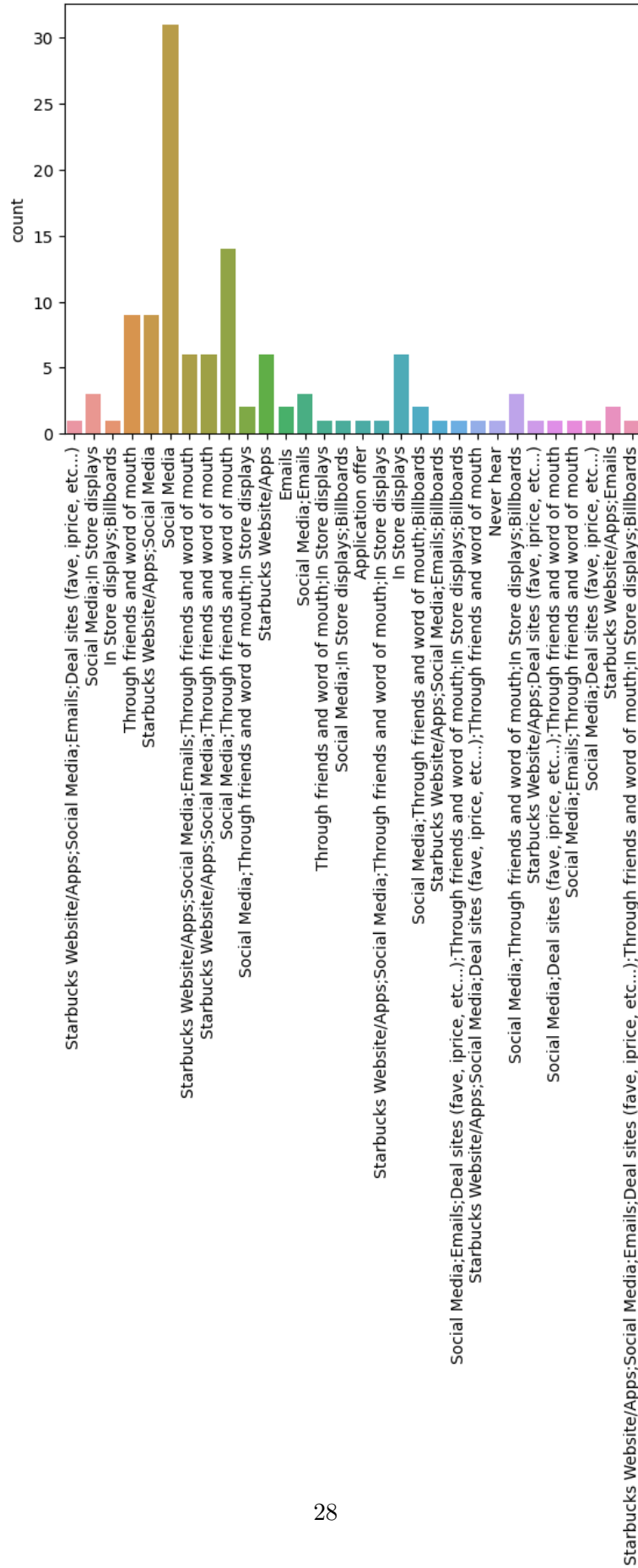
CountPlot for the column: Frequent_Product



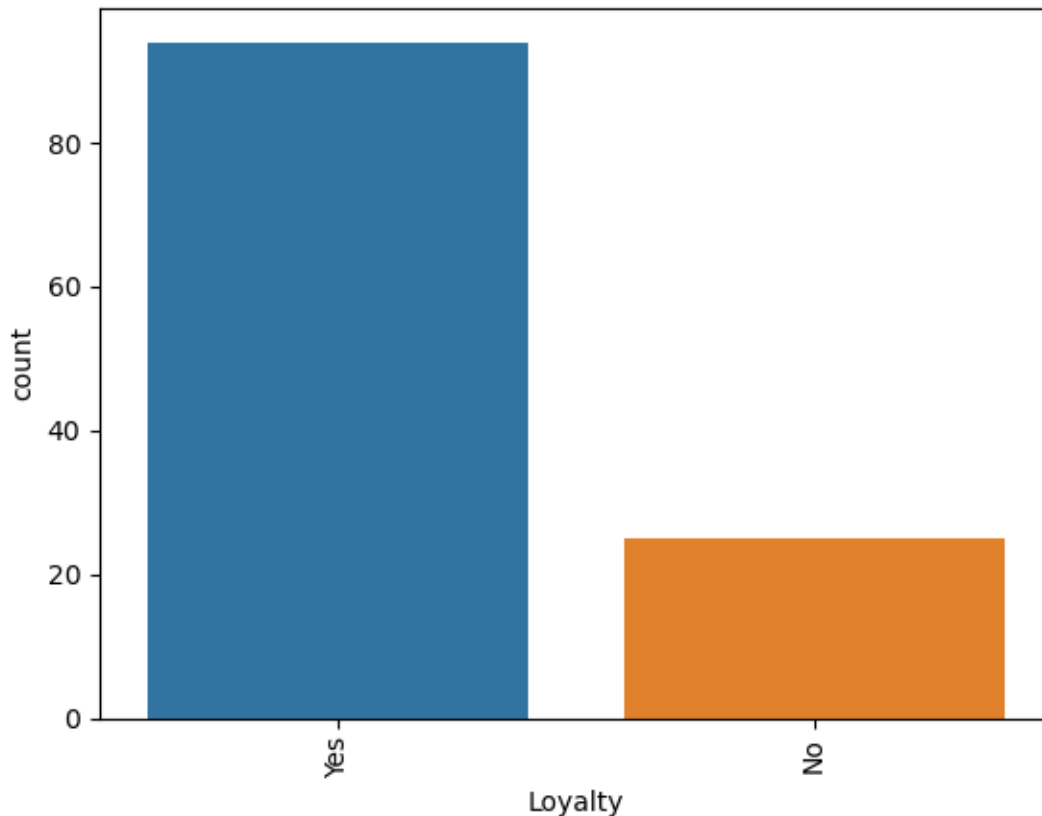
CountPlot for the column: Avg_Money_Spent



CountPlot for the column: Promotion_Source



CountPlot for the column: Loyalty



- Both Females and Males customer are comparable in count
- Customers between age 20 to 29 are the majority customers then 30 to 40 age. 40 and above age group are less interested in the products
- Employees and Students are more interested in the products compared to Self-employed. Ignore Housewife as the category has too less in count to consider to draw insights
- Customers with annual income below RM50000 are the potential customers
- Most of the customers visit rarely. Monthly visitors are also significant in number. Daily visitors are very less in count
- Take away customers are very high next comes the Drive In and then Drive thru categories
- Majority customers spend less than an hour. Very few people spend time around an hour to two
- Majority of customers are more than 3km distance from the store.
- Customers with membership are almost in number to no membership customers
- Coffee, Cold drinks, Pastries seems to be the frequently bought products in Store
- Majority of people spend money less than RM20. Customer count spending more money decreases with increase in Money
- Social media is the main source of Promotion for the products

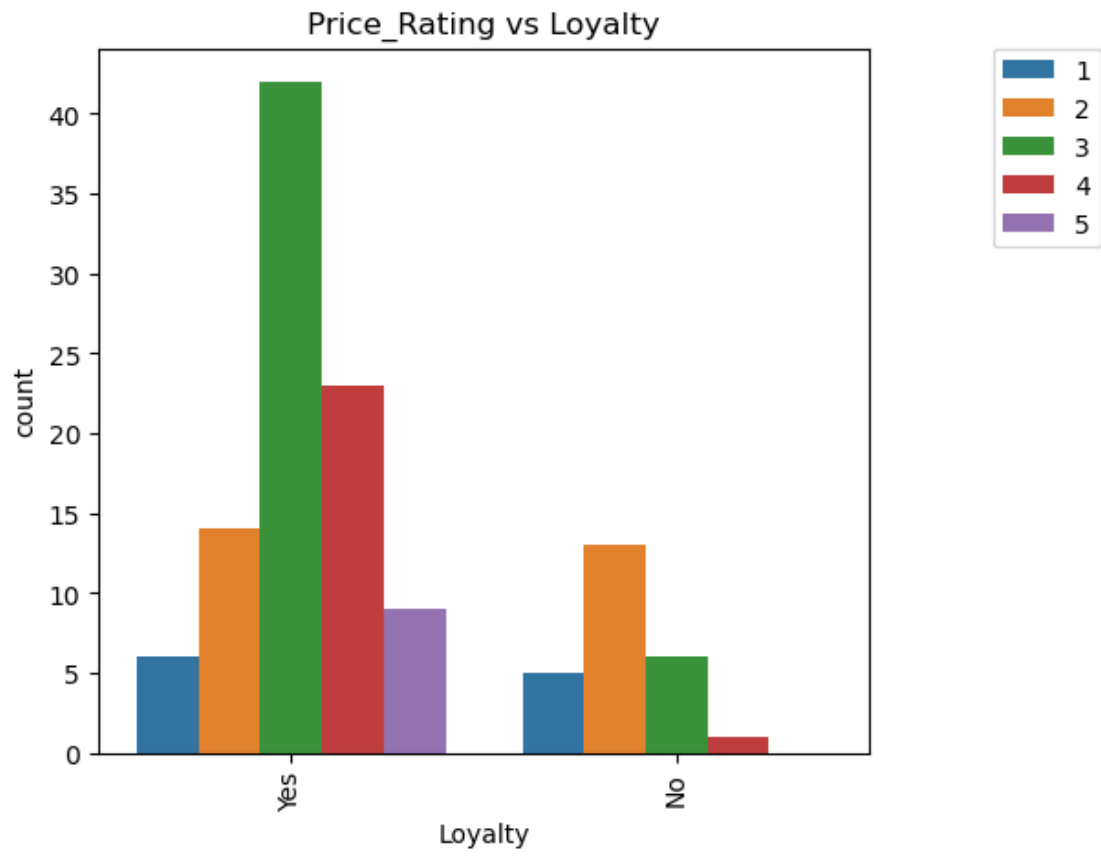
- Interestingly, even the customers having/not having membership are equal in number, majority of customers are loyal to our brand

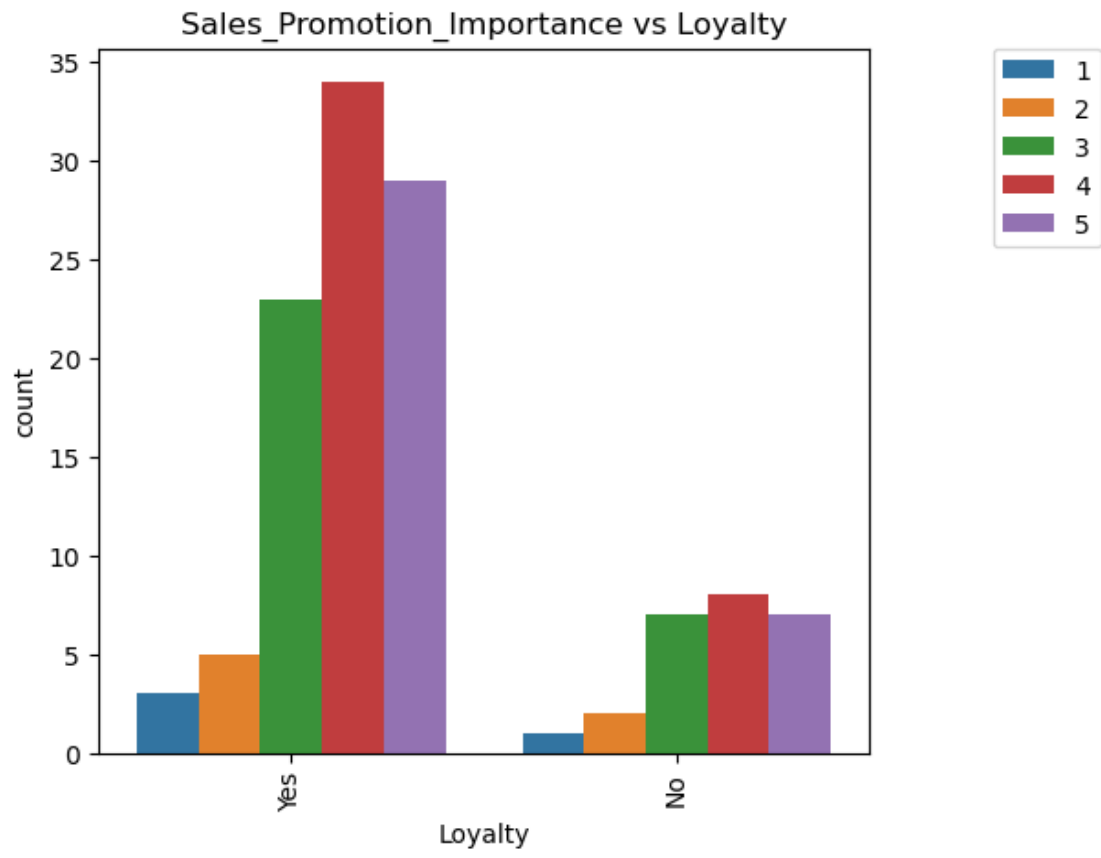
Bi-Variate Analysis

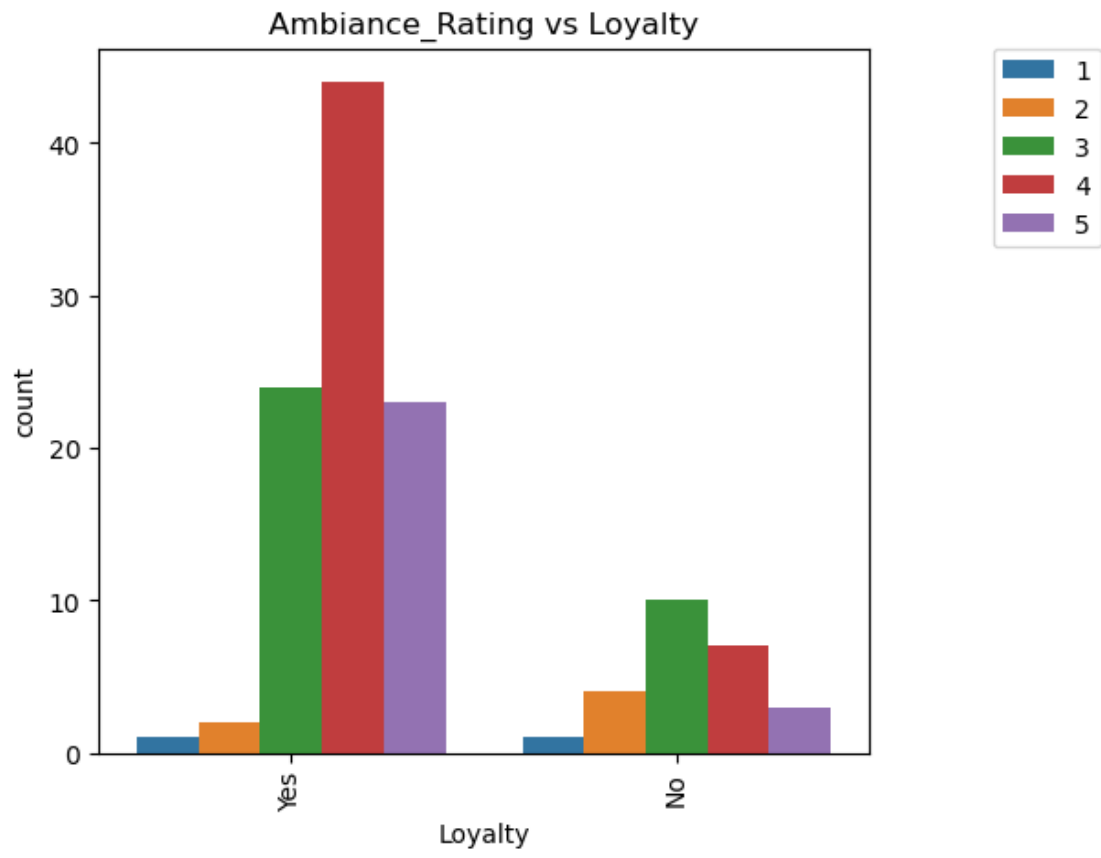
[]:

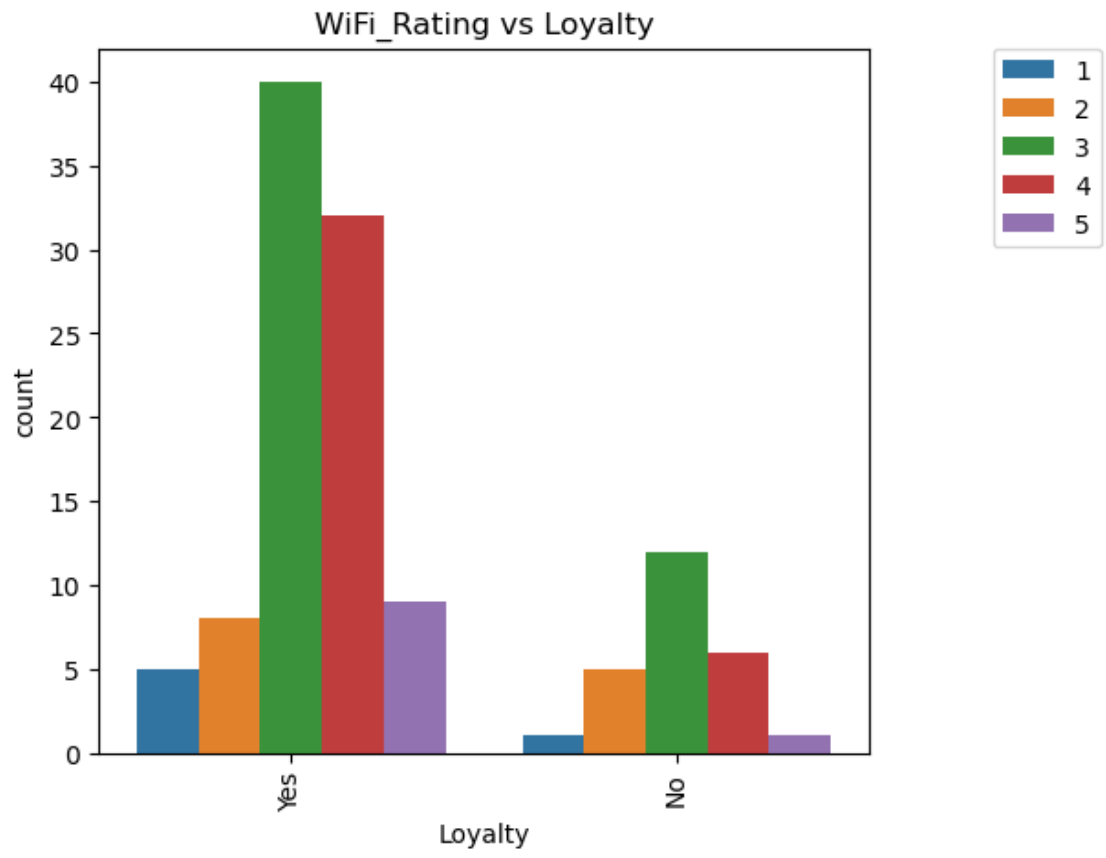
```
[85]: hue_order=['1','2','3','4','5']
      for i in num_cols:
          df[i]=df[i].astype(str)
          plt.figure(figsize=(25,5))
          plt.subplot(1,4,1)
          sns.countplot(x=df.Loyalty, hue=df[i], hue_order=hue_order)
          plt.title(i+" vs Loyalty")
          plt.xticks(rotation=90)
          plt.legend(bbox_to_anchor=(1.3,1), borderaxespad=0)
          plt.show()
```

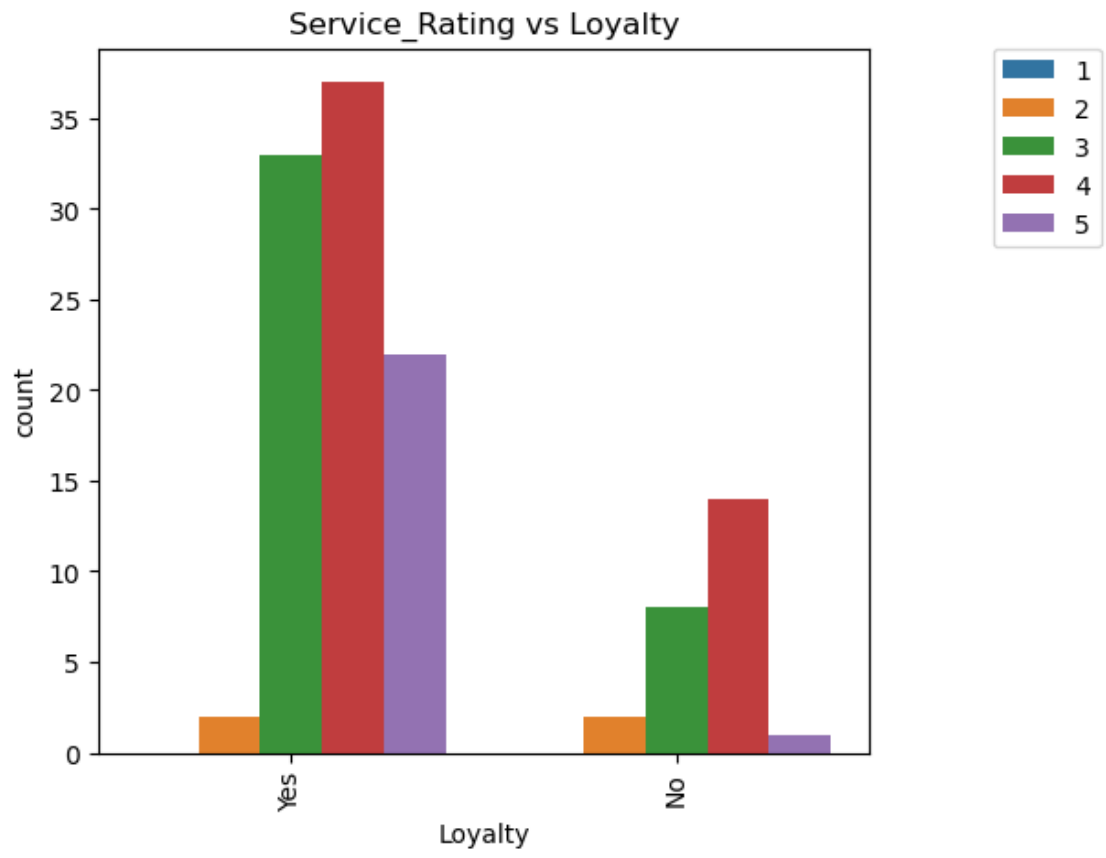


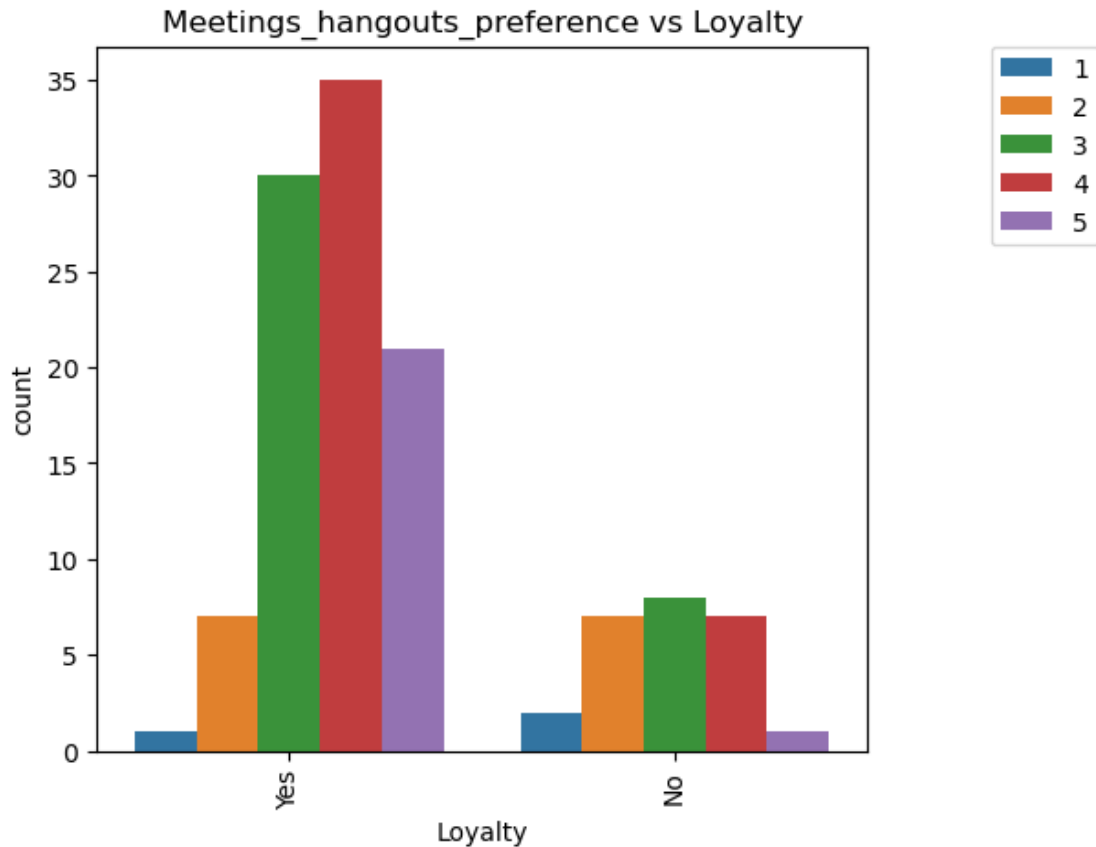










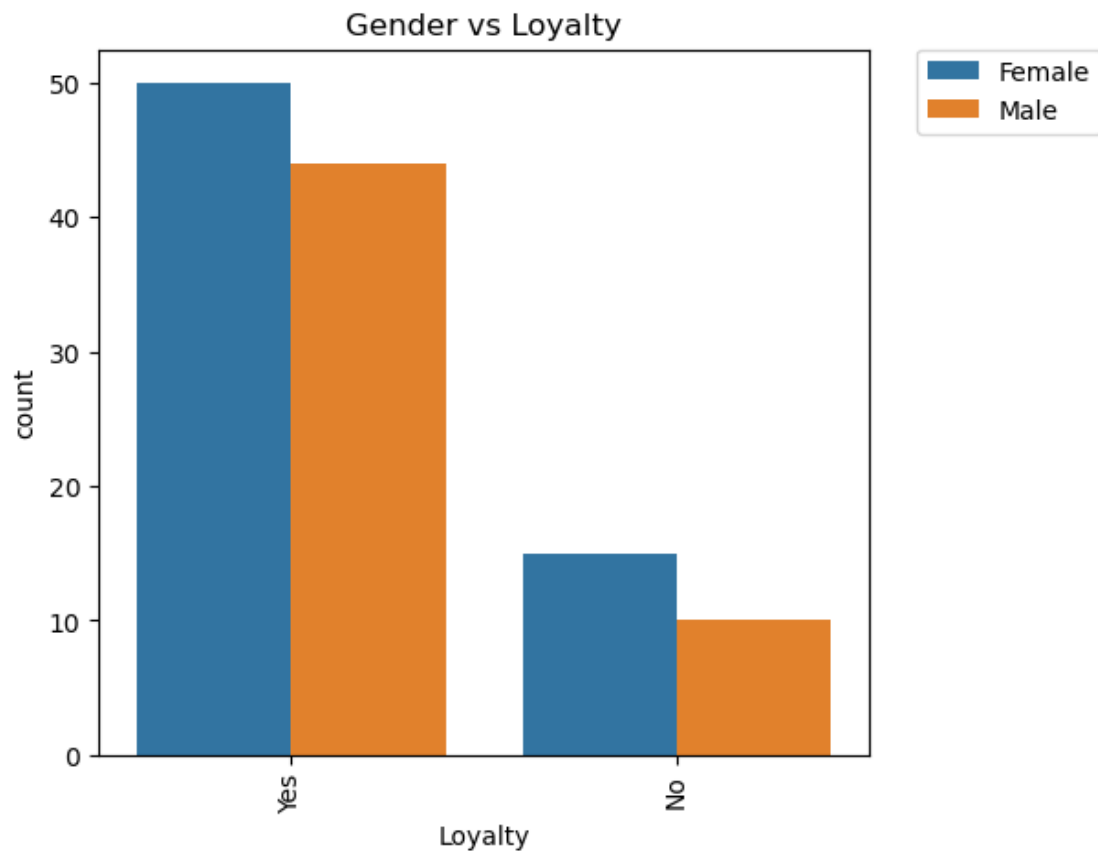


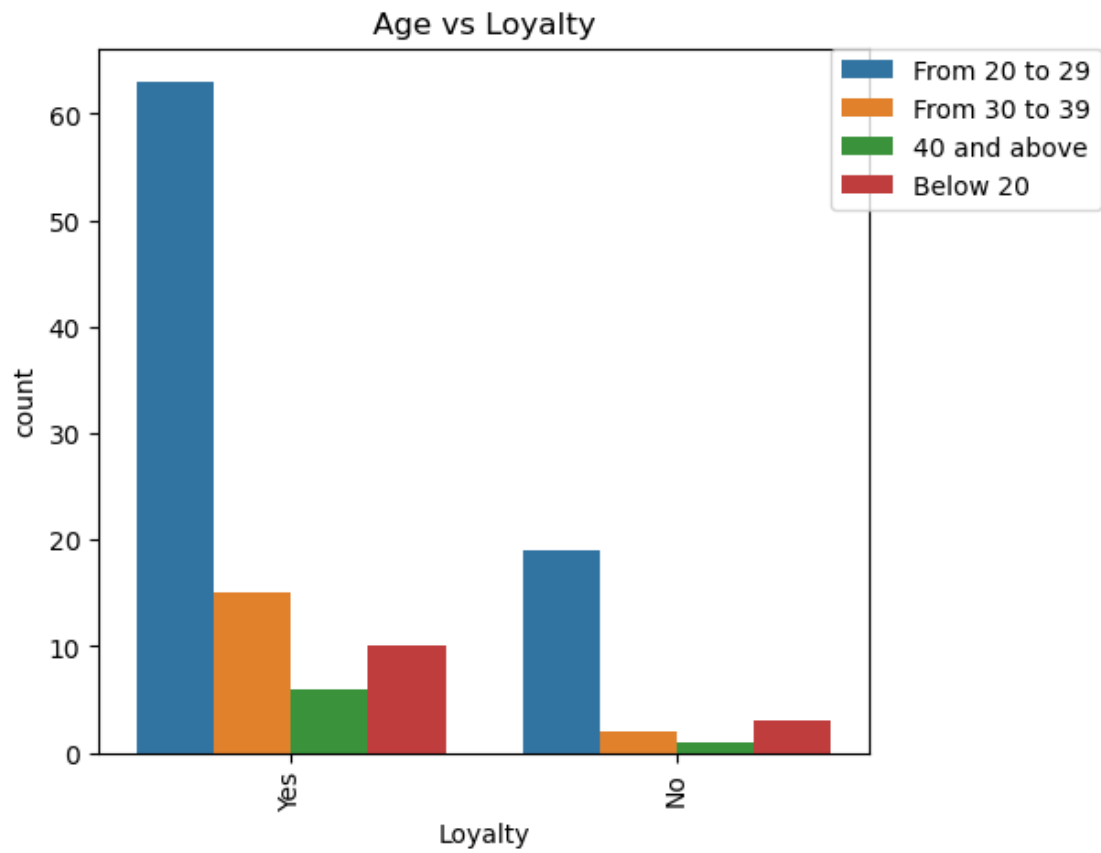
Among the loyal customer

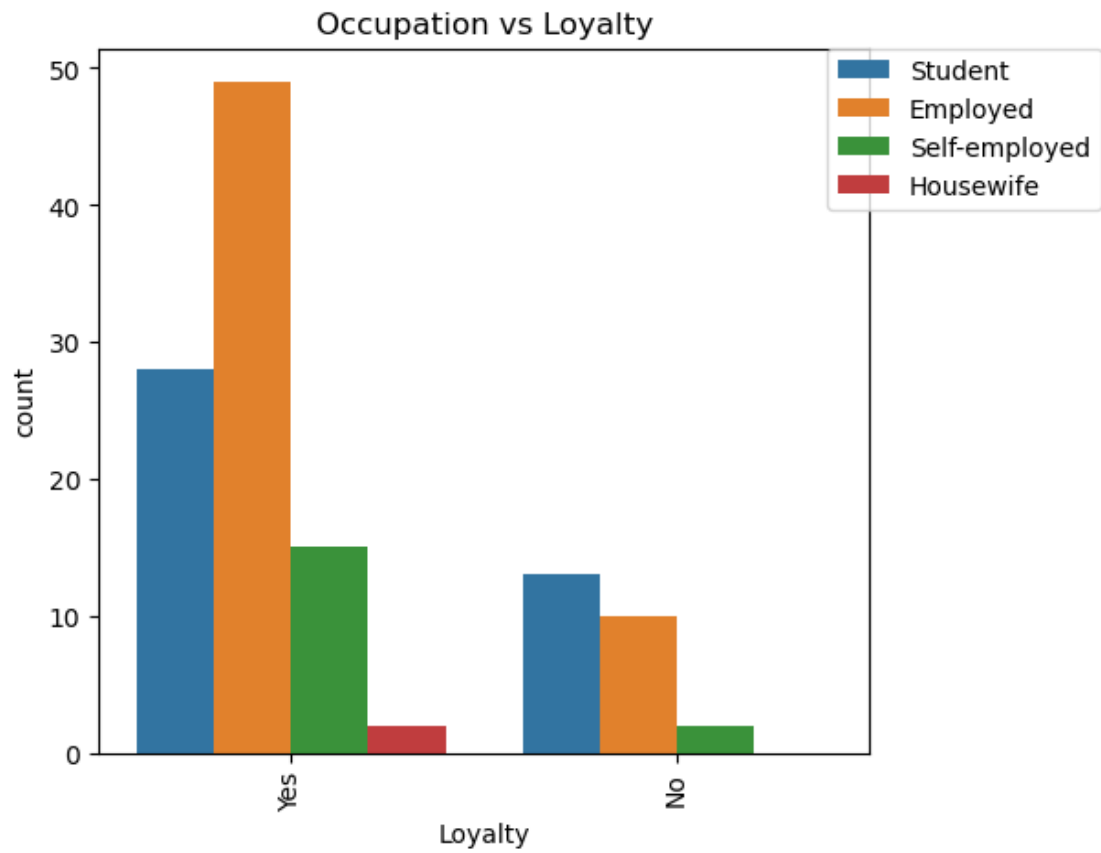
- 4 is the most common quality rating
- 3 is the most common price rating and price rating of 5 are loyal customers
- 4 is the most common ambiance rating ##### Among the Non_Loyal customers
- 3 is the most common quality rating
- 2 is the most common price rating
- 3 is the most common ambiance rating
- Loyalty doesn't seem to depend on wifi rating and sales promotion much
- Customers giving Service rating 5 have more likely loyal customers. The likeliness seems to be decreasing with decreasing rating
- Customers with meeting_hangout_preference 4 are more likely loyal

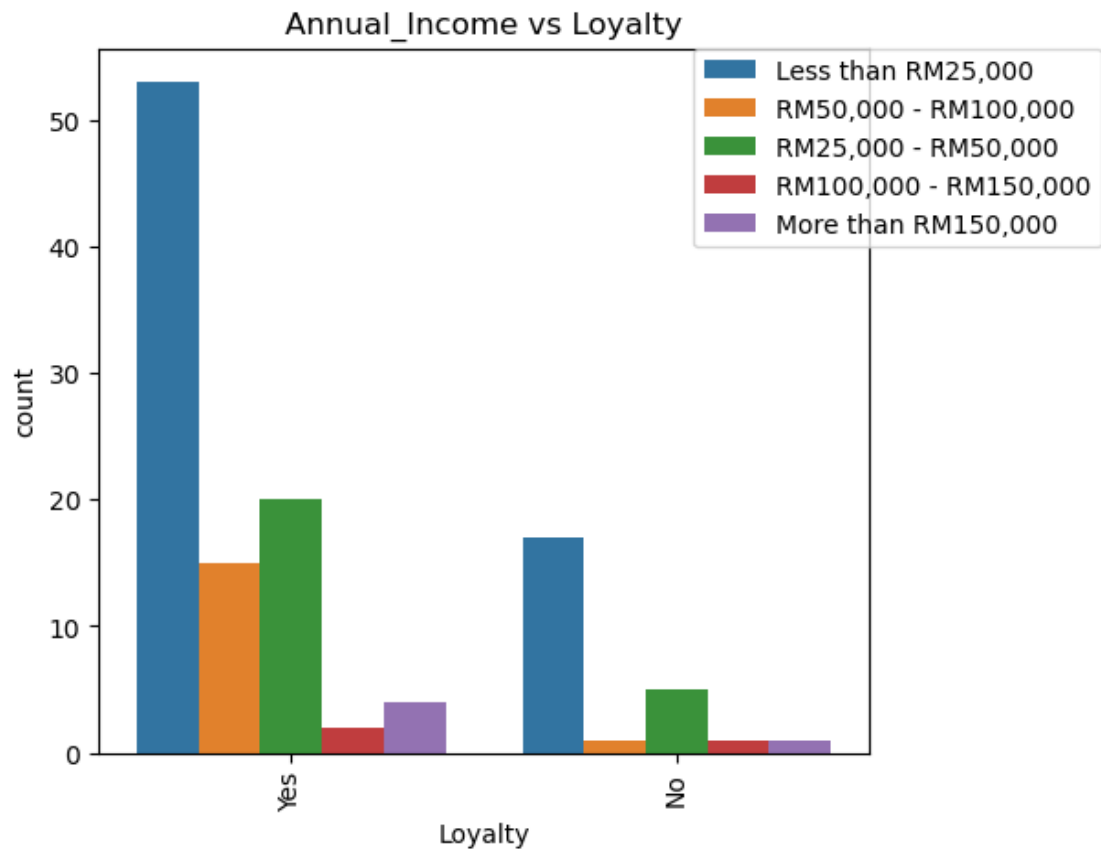
Lets analyse the categorical columns

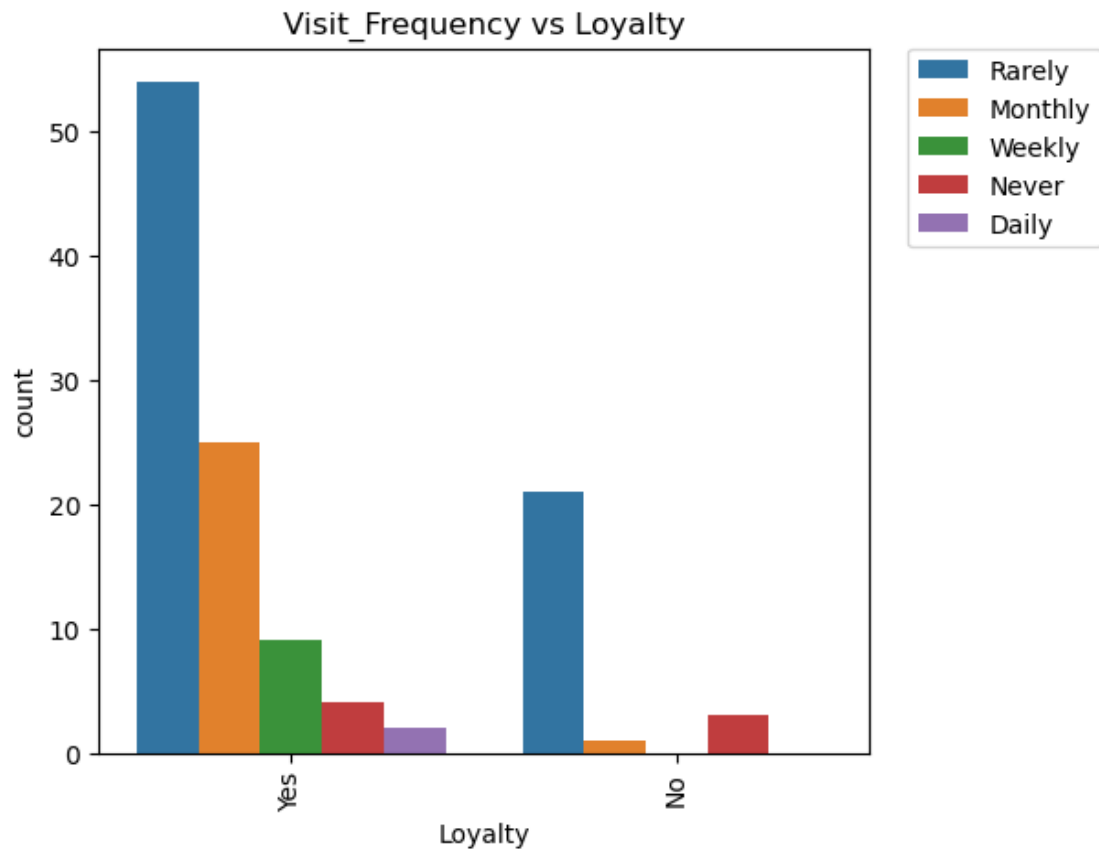
```
[69]: for i in cat_cols[1:]:  
    plt.figure(figsize=(25,5))  
    plt.subplot(1,4,1)  
    sns.countplot(x=df.Loyalty, hue=df[i])  
    plt.title(i+" vs Loyalty")  
    plt.xticks(rotation=90)  
    plt.legend(bbox_to_anchor=(1.3,1), borderaxespad=0)  
    plt.show()
```

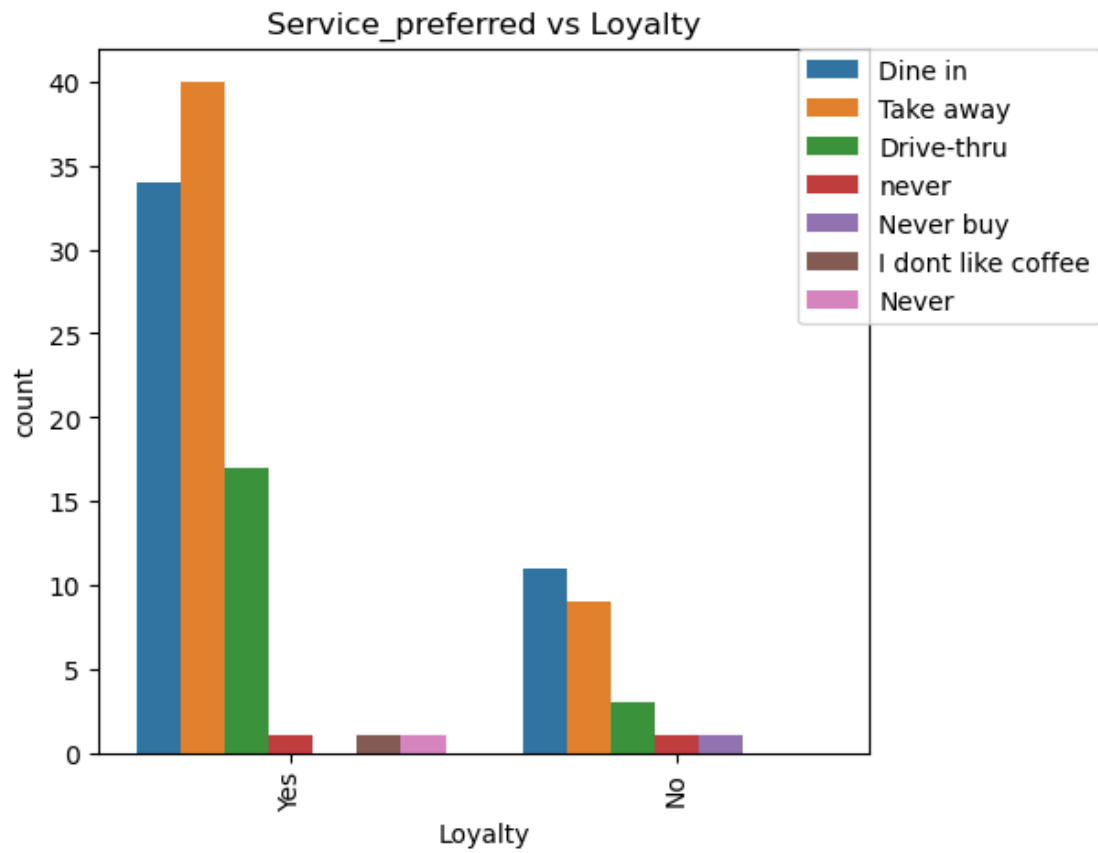


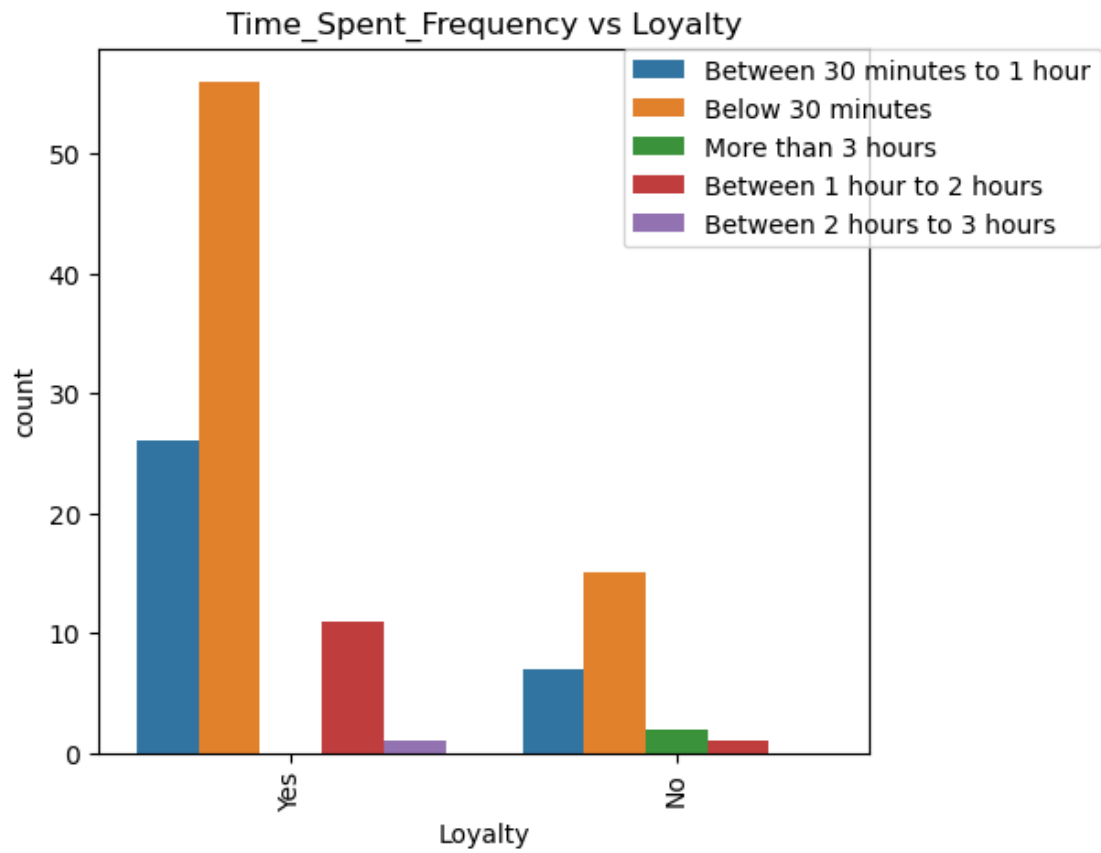


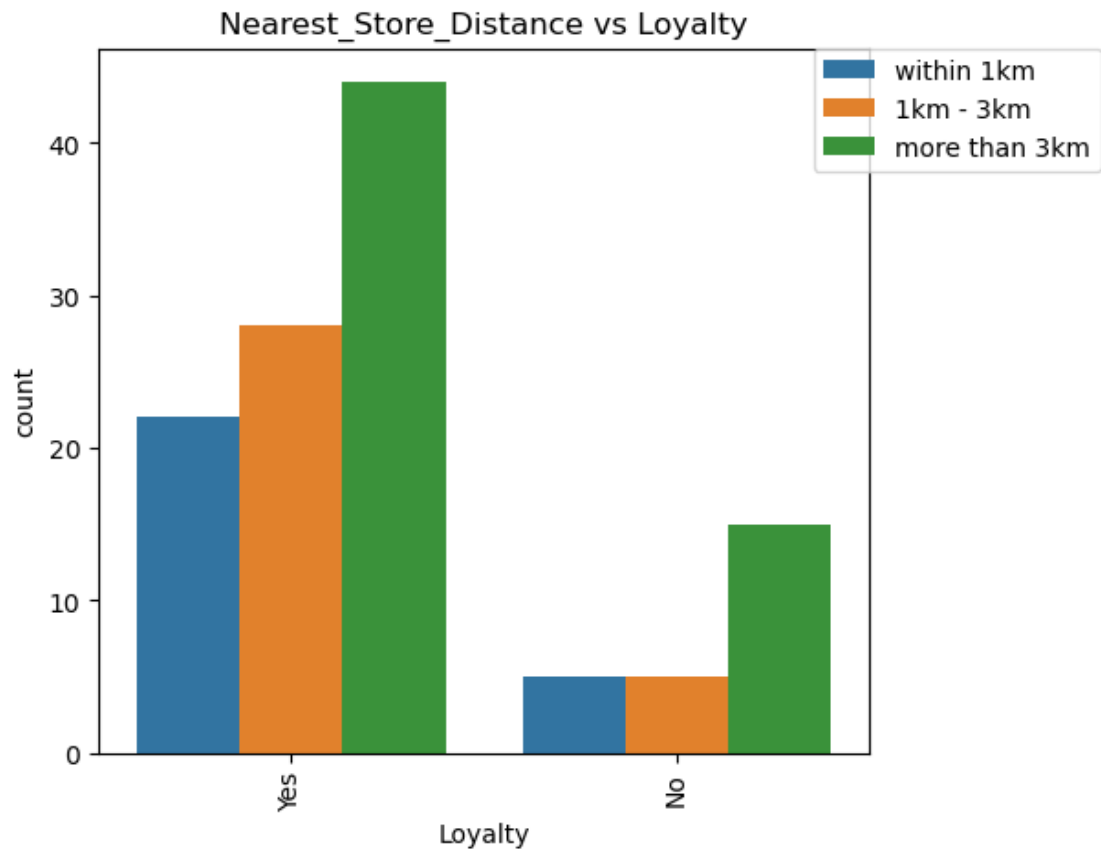


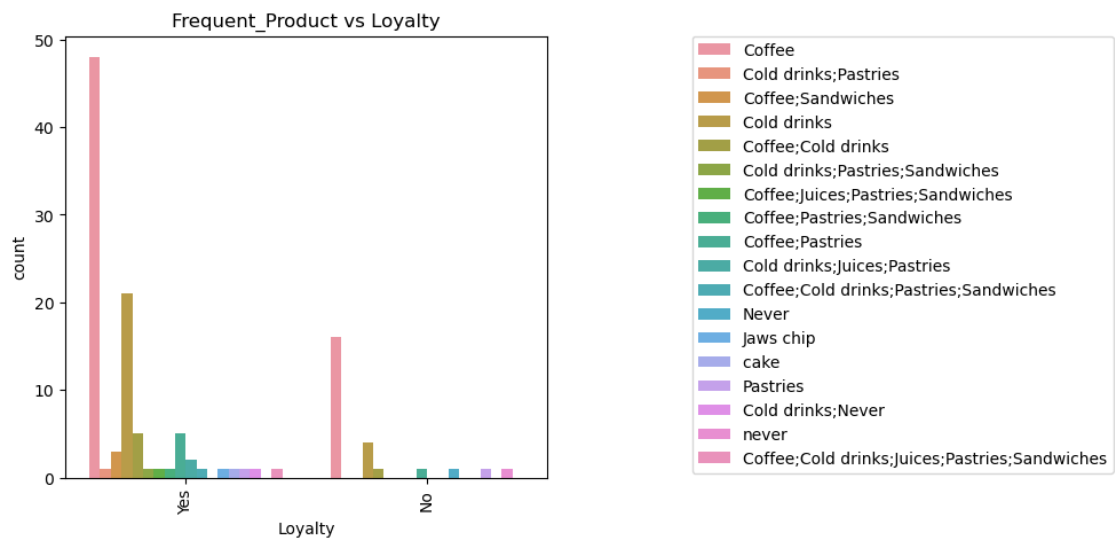
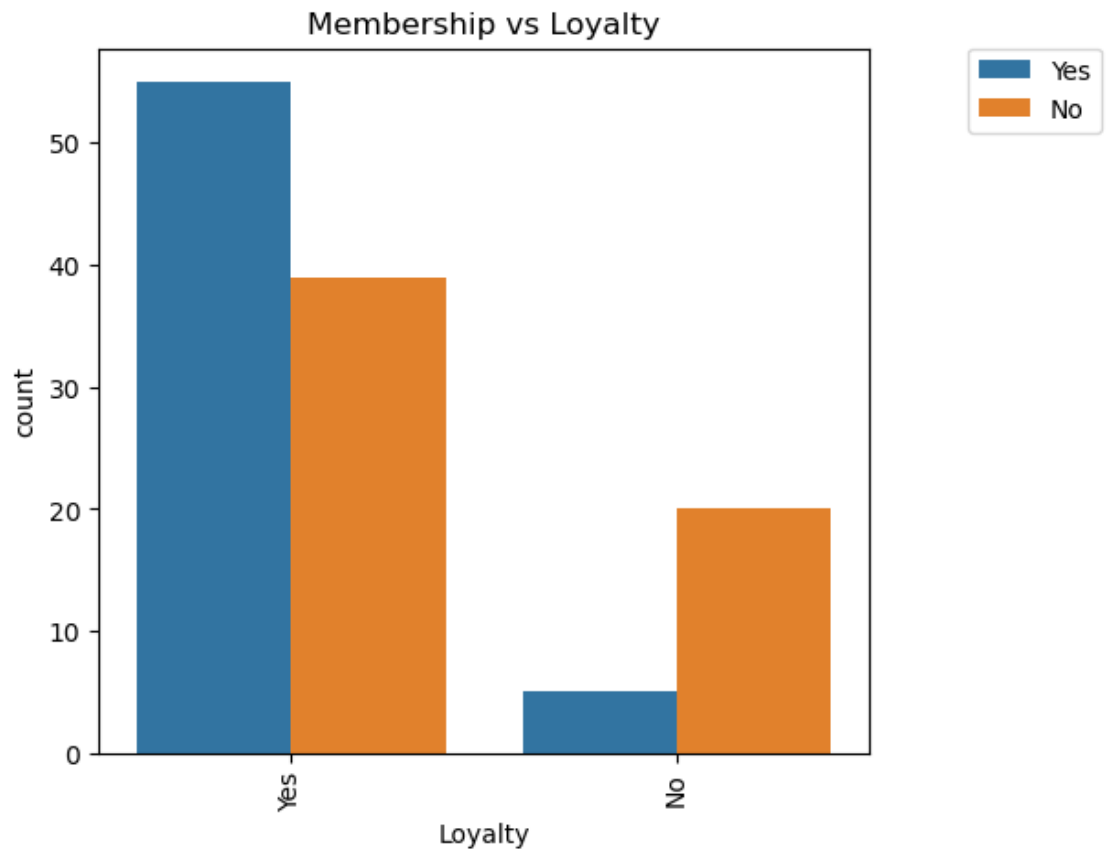


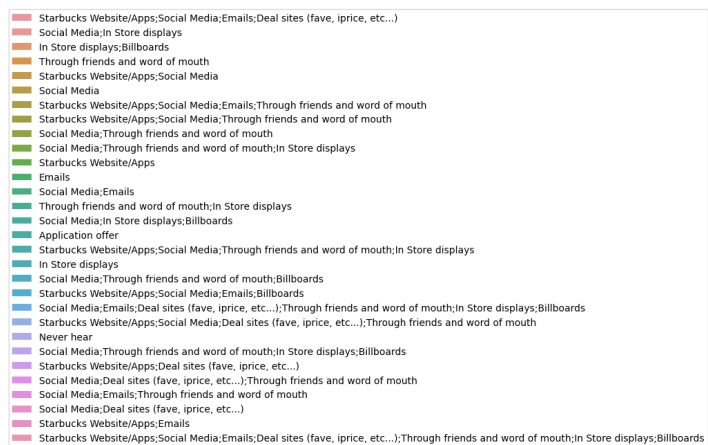
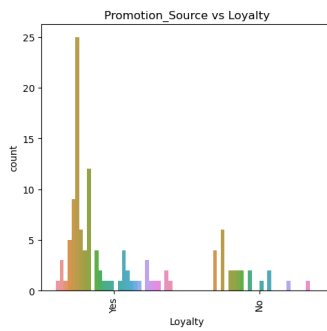
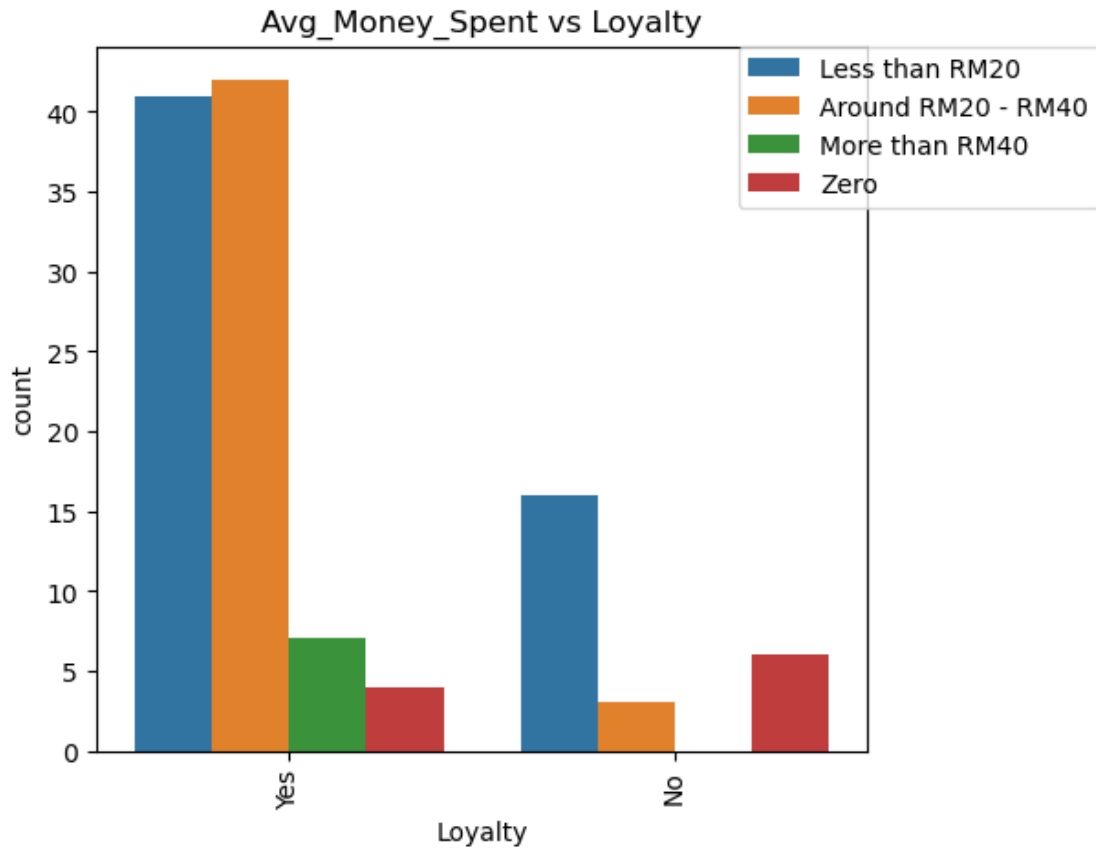


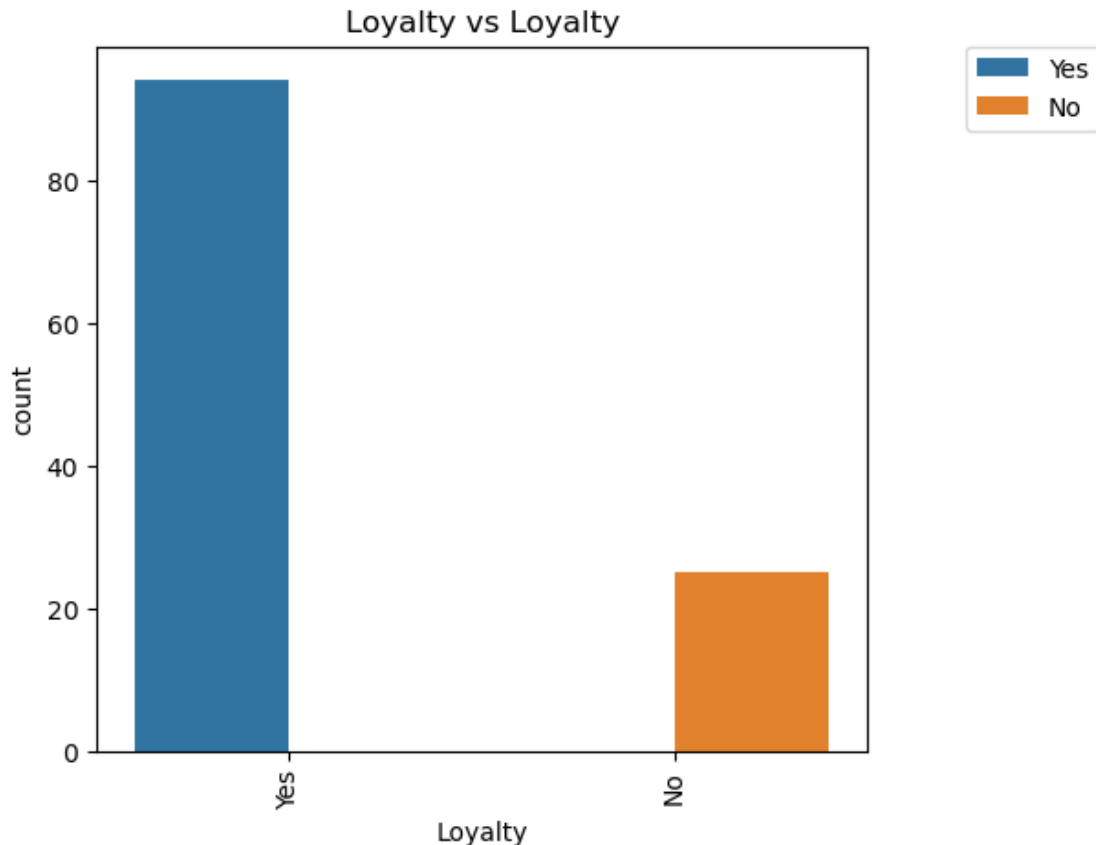












- Gender doesn't seem to have impact on the Loyalty. Female customers are more in number
- Customers from age group 20-29 are major segment next comes 30-39 among both loyal and non-loyal customers
- Employed customers are major category among loyal customers whereas Students are major category among non-loyal customers
- Customers with annual income 50k-100k are more in number among loyal customers
- Customers with visit frequency rarely
- Take away is the majority among loyal customers, whereas Dine in Non-Loyal customers
- Time spent and nearest store distance doesn't seem to have much influence on the loyalty. To be analysed further
- Customers with membership are more loyal
- Coffee, cold drinks, pastries are major categories of frequently bought products
- Customers spent money more than RM20 are more loyal
- Social Media is the major Promotion source

Multi-Variate Analysis

```
[86]: def plot_fun(df, col1, col2, col3):

    plot_df = df[[col1, col2, col3]]
    plot_df['dummy'] = np.ones(len(plot_df), dtype=int)
```

```

plot_df

grouped_plot = plot_df.groupby([col1, col2, col3]).count().unstack(level=2)
grouped_plot

loyalty = grouped_plot.columns.levels[1]
colors = [plt.get_cmap('viridis')(i) for i in np.linspace(0,1,len(loyalty))]
colors

sns.set(context='talk')
nxplots = len(grouped_plot.index.levels[0])
nyplots = len(grouped_plot.index.levels[1])
fig, axes = plt.subplots(nrows=nxplots, ncols=nyplots, sharex=True,
↪sharey=True, figsize=(12,10))
fig.suptitle(col1 + ' vs ' + col2 + ' vs ' + col3)

for a,i in enumerate(grouped_plot.index.levels[0]):
    for b,j in enumerate(grouped_plot.index.levels[1]):
        try:
            axes[a,b].bar(grouped_plot.columns.levels[1], grouped_plot.
↪loc[i,j], color=colors)
            print(i,j)
            axes[a,b].xaxis.set_ticks([])
        except:
            pass

axeslabel = fig.add_subplot(111, frameon=False)
plt.tick_params(labelcolor='none')
plt.grid(False)
axeslabel.set_ylabel(col1,rotation='horizontal',y=1,weight="bold")
axeslabel.set_xlabel(col2,y=1,weight="bold")
for i, j in enumerate(grouped_plot.index.levels[1]):
    axes[-1,i].set_xlabel(j, rotation=90)
for i, j in enumerate(grouped_plot.index.levels[0]):
    axes[i,0].set_ylabel(j, rotation=90)

fig.subplots_adjust(right=0.82)

fig.legend([Patch(facecolor = i) for i in colors],
           grouped_plot.columns.levels[1],
           title="Loyalty",
           loc="center right")
print(grouped_plot)

```

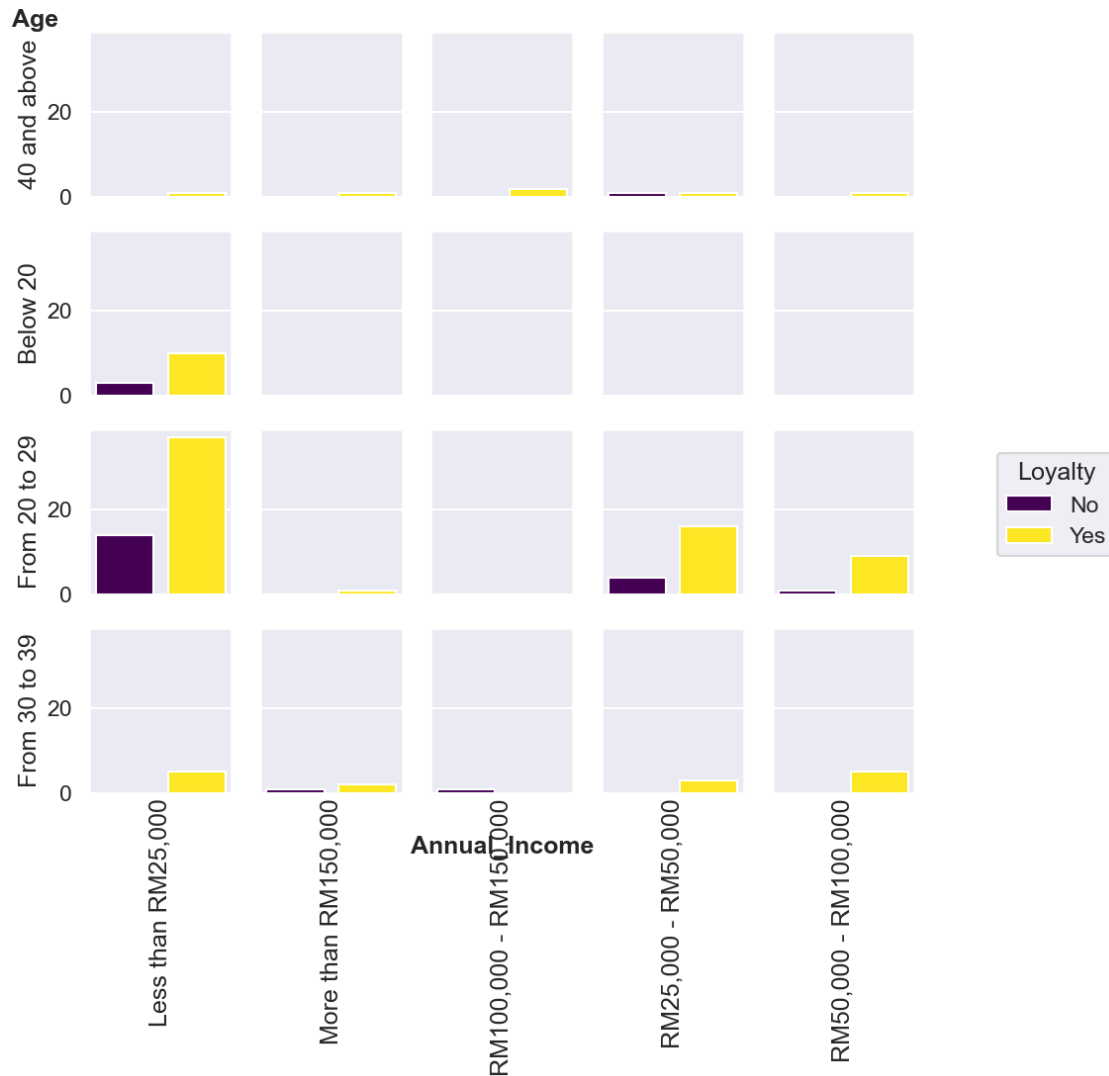
age_vs_AnnualIncome_vs_Loyalty

```
[87]: plot_fun(df, 'Age', 'Annual_Income', 'Loyalty')
```


40 and above Less than RM25,000
 40 and above More than RM150,000
 40 and above RM100,000 - RM150,000
 40 and above RM25,000 - RM50,000
 40 and above RM50,000 - RM100,000
 Below 20 Less than RM25,000
 From 20 to 29 Less than RM25,000
 From 20 to 29 More than RM150,000
 From 20 to 29 RM25,000 - RM50,000
 From 20 to 29 RM50,000 - RM100,000
 From 30 to 39 Less than RM25,000
 From 30 to 39 More than RM150,000
 From 30 to 39 RM100,000 - RM150,000
 From 30 to 39 RM25,000 - RM50,000
 From 30 to 39 RM50,000 - RM100,000

		dummy	
Loyalty		No	Yes
Age	Annual_Income		
40 and above	Less than RM25,000	NaN	1.0
	More than RM150,000	NaN	1.0
	RM100,000 - RM150,000	NaN	2.0
	RM25,000 - RM50,000	1.0	1.0
	RM50,000 - RM100,000	NaN	1.0
Below 20	Less than RM25,000	3.0	10.0
From 20 to 29	Less than RM25,000	14.0	37.0
	More than RM150,000	NaN	1.0
	RM25,000 - RM50,000	4.0	16.0
	RM50,000 - RM100,000	1.0	9.0
From 30 to 39	Less than RM25,000	NaN	5.0
	More than RM150,000	1.0	2.0
	RM100,000 - RM150,000	1.0	NaN
	RM25,000 - RM50,000	NaN	3.0
	RM50,000 - RM100,000	NaN	5.0

Age vs Annual_Income vs Loyalty



- Age group 20-29 is the majority group. Their loyalty percentage is increasing with the increase in salary
- Age group below 20 customers have income less than RM25000
- Customer interest in the products is decreasing with the increase in age from 20

age_vs_Occupation_vs_Loyalty

```
[88]: plot_fun(df, 'Age', 'Occupation', 'Loyalty')
```

```
40 and above Employed
40 and above Housewife
40 and above Self-employed
Below 20 Student
```

From 20 to 29 Employed
 From 20 to 29 Housewife
 From 20 to 29 Self-employed
 From 20 to 29 Student
 From 30 to 39 Employed
 From 30 to 39 Self-employed
 From 30 to 39 Student

		dummy	
Loyalty		No	Yes
Age	Occupation		
40 and above	Employed	NaN	2.0
	Housewife	NaN	1.0
	Self-employed	1.0	3.0
Below 20	Student	3.0	10.0
From 20 to 29	Employed	8.0	37.0
	Housewife	NaN	1.0
	Self-employed	1.0	10.0
	Student	10.0	15.0
From 30 to 39	Employed	2.0	10.0
	Self-employed	NaN	2.0
	Student	NaN	3.0

Age vs Occupation vs Loyalty



- Among customers from age group 20-29 Employed are the majority group next comes Student and then Self-Employed
- Even the Self-Employed are less in count they have high loyalty percentage then comes Employees. Students have high negative responses
- Customers below age group 20 have significantly high positive response
- Customers from age group 30-39 have good positive response

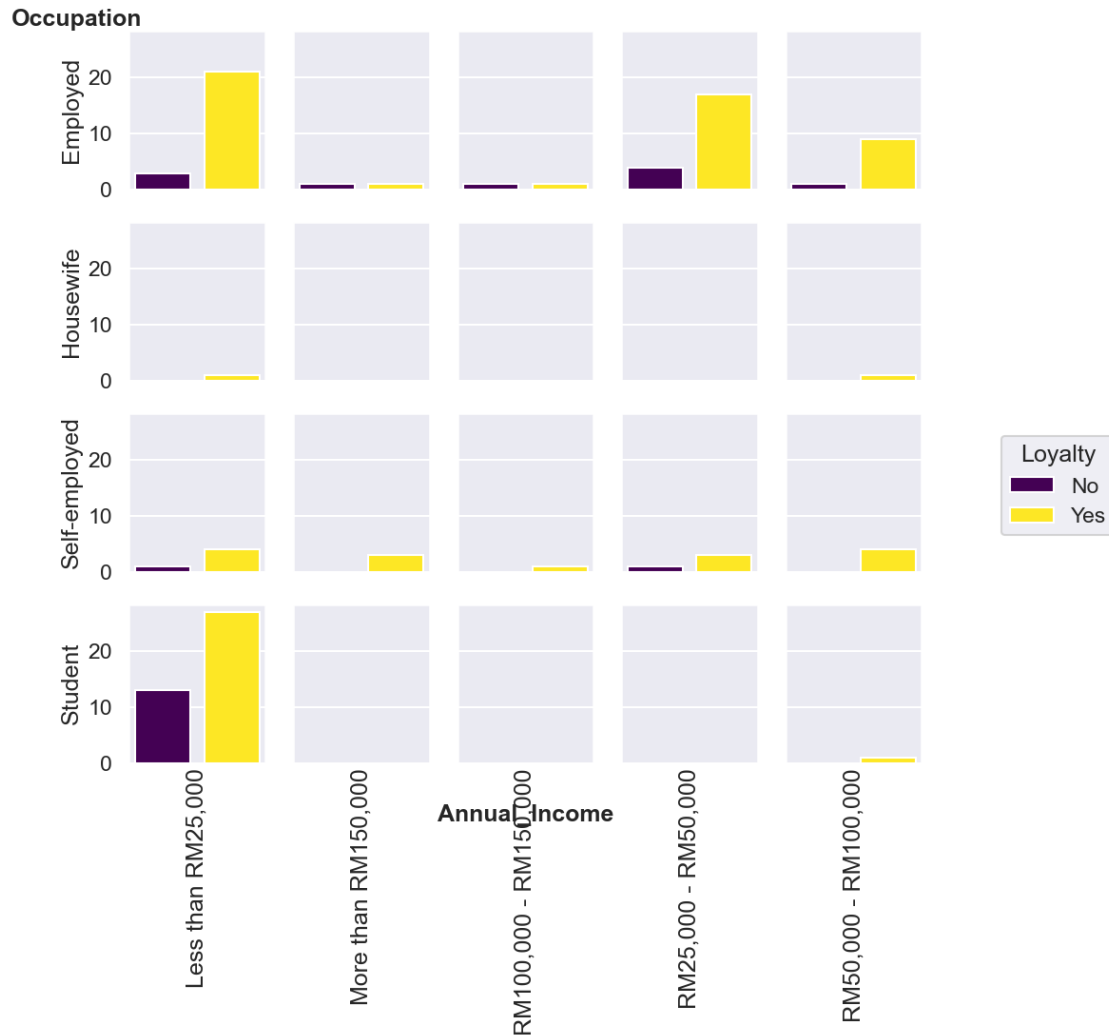
Occupation_vs_AnnualIncome_vs_Loyalty

```
[89]: plot_fun(df, 'Occupation', 'Annual_Income', 'Loyalty')
```

```
Employed Less than RM25,000
Employed More than RM150,000
Employed RM100,000 - RM150,000
Employed RM25,000 - RM50,000
Employed RM50,000 - RM100,000
```

Housewife Less than RM25,000			
Housewife RM50,000 - RM100,000			
Self-employed Less than RM25,000			
Self-employed More than RM150,000			
Self-employed RM100,000 - RM150,000			
Self-employed RM25,000 - RM50,000			
Self-employed RM50,000 - RM100,000			
Student Less than RM25,000			
Student RM50,000 - RM100,000			
		dummy	
Loyalty		No	Yes
Occupation	Annual_Income		
Employed	Less than RM25,000	3.0	21.0
	More than RM150,000	1.0	1.0
	RM100,000 - RM150,000	1.0	1.0
	RM25,000 - RM50,000	4.0	17.0
	RM50,000 - RM100,000	1.0	9.0
Housewife	Less than RM25,000	NaN	1.0
	RM50,000 - RM100,000	NaN	1.0
Self-employed	Less than RM25,000	1.0	4.0
	More than RM150,000	NaN	3.0
	RM100,000 - RM150,000	NaN	1.0
	RM25,000 - RM50,000	1.0	3.0
	RM50,000 - RM100,000	NaN	4.0
Student	Less than RM25,000	13.0	27.0
	RM50,000 - RM100,000	NaN	1.0

Occupation vs Annual_Income vs Loyalty



- Customers from Employeed category having income less than RM50000 have high postitive response
- Students have income less than RM250000 and they are high postive response as well signif-icant negative response

We have seens the Females and Males are comparale in count. Lets find out the if there are any interesting factors

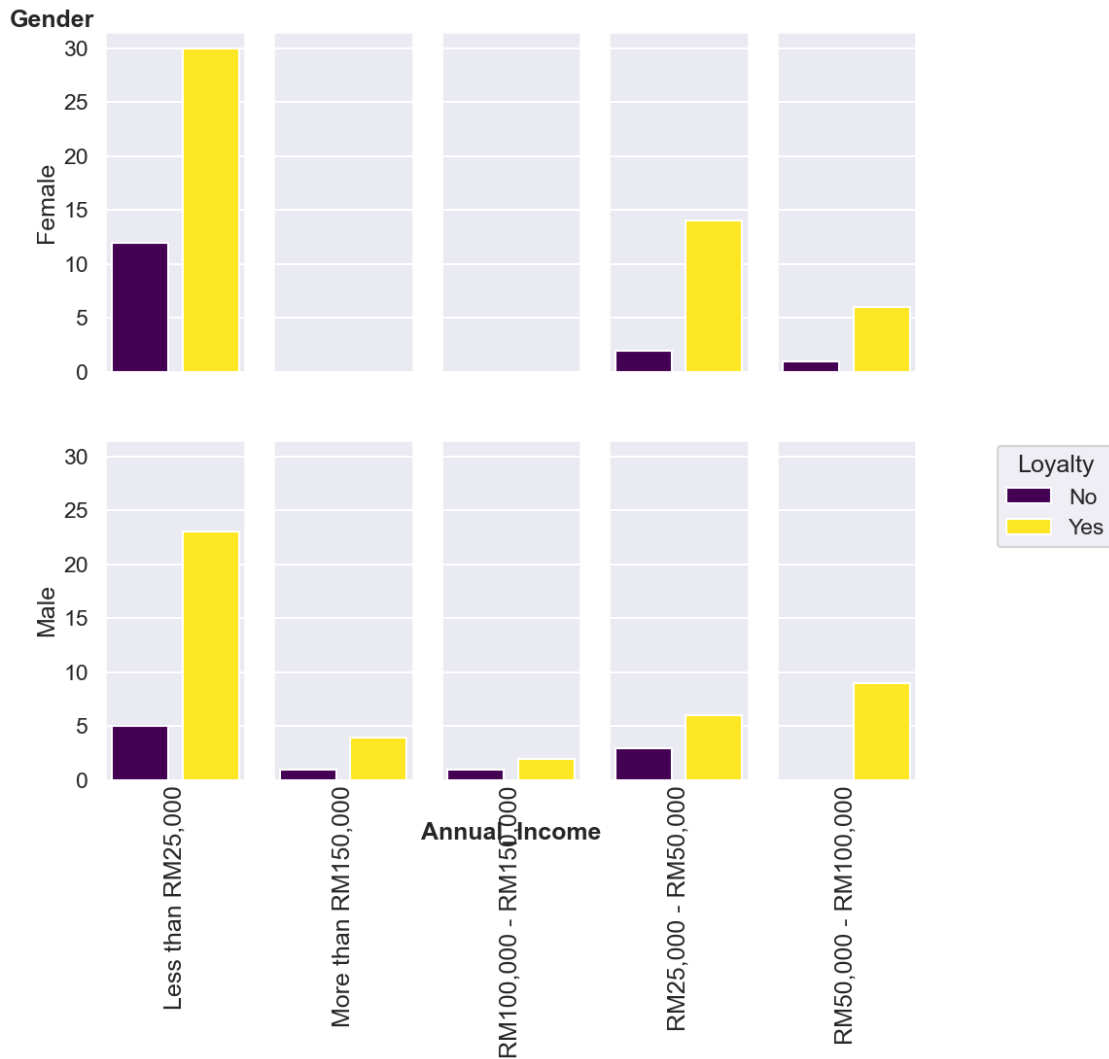
Gender_vs_AnnualIncome_vs_Loyalty

```
[90]: plot_fun(df, 'Gender', 'Annual_Income', 'Loyalty')
```

Female Less than RM25,000
 Female RM25,000 - RM50,000
 Female RM50,000 - RM100,000

Male Less than RM25,000			
Male More than RM150,000			
Male RM100,000 - RM150,000			
Male RM25,000 - RM50,000			
Male RM50,000 - RM100,000			
		dummy	
Loyalty		No	Yes
Gender Annual_Income			
Female	Less than RM25,000	12.0	30.0
	RM25,000 - RM50,000	2.0	14.0
	RM50,000 - RM100,000	1.0	6.0
Male	Less than RM25,000	5.0	23.0
	More than RM150,000	1.0	4.0
	RM100,000 - RM150,000	1.0	2.0
	RM25,000 - RM50,000	3.0	6.0
	RM50,000 - RM100,000	NaN	9.0

Gender vs Annual_Income vs Loyalty



- Female customers are more loyal than Male customers
- Above 100000 we seem to have more male customers than Females

Lets understand the difference in the Male and Female loyalty based on their age, Occupation, Annual_Income details

Lets convert the Loyalty column values yes to 1 and No to 0 Also create Loyalty_invert column with values yes as 0 and No as 1

```
[91]: df.Loyalty = df.Loyalty.apply(lambda x: 1 if x=='Yes' else 0)
df['Loyalty_invert'] = df.Loyalty.apply(lambda x: 1 if x==0 else 0)
df.Loyalty_invert.value_counts()
```

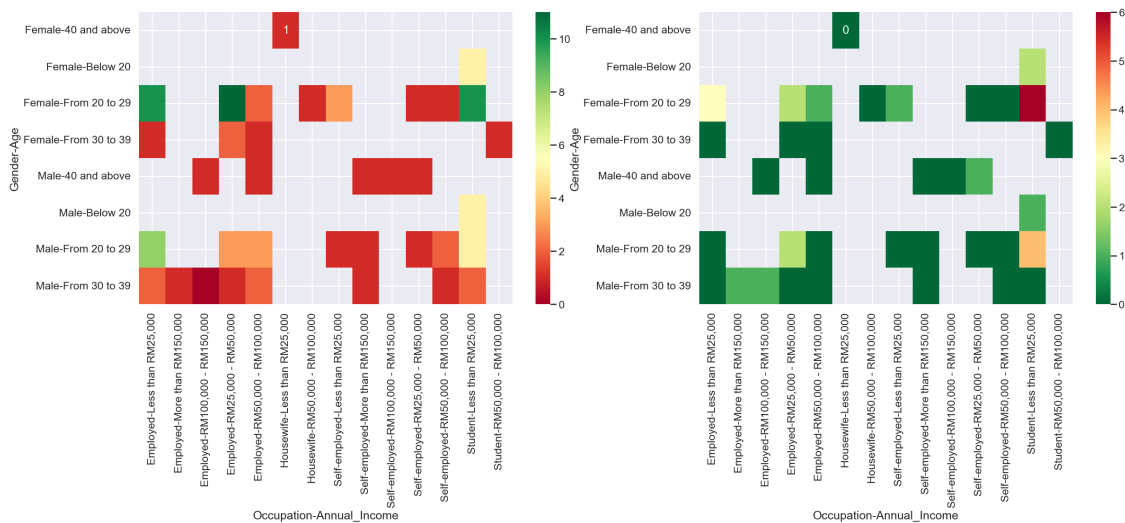


```
[91]: Loyalty_invert
0    94
1    25
Name: count, dtype: int64
```

Gender_vs_Age_vs_Occupation_vs_Annual_Income_vs_Loyalty

```
[92]: pivot_df = pd.pivot_table(data=df, index=['Gender', 'Age'],
    ↪columns=['Occupation', 'Annual_Income'], values='Loyalty', aggfunc='sum')

plt.figure(figsize=(28,8))
plt.subplot(1,2,1)
sns.heatmap(data=pivot_df, cmap='RdYlGn', annot=True)
pivot_df = pd.pivot_table(data=df, index=['Gender', 'Age'],
    ↪columns=['Occupation', 'Annual_Income'], values='Loyalty_invert',
    ↪aggfunc='sum')
plt.subplot(1,2,2)
sns.heatmap(data=pivot_df, cmap='RdYlGn_r', annot=True)
plt.show()
```



- Female in 20-29 age have 10 positive responses and 3 negative responses. They are employees with income less than RM25000
- Female in 20-29 age have 11 positive responses and 2 negative responses. They are employees with income greater than RM25000 and less then RM50000
- Employed Males of age 20 to 29 and income less than RM25000 have no negative response. Whereas Males of same categories except income ranging between RM25000 to RM 50000 almost equal positive and negative responses(3+vs, 2-vs)
- Males from 30 to 39 age from students lessthanRM25000 have almost equal positive and negative responses(5+vs, 4-vs)
- Females from 20-29 who are students and income less than RM25000 have high positive and

negative responses

- we can see only one 0 in the left heat map and corresponding value in the right heap map has either zero or less number. This says that all the different categories are having high loyal customers

lets check the different factors for the category female student, age 20-29 with income less than RM25000

```
[93]: df3 = df.loc[(df.Gender== 'Female')&(df.Occupation == 'Student') & (df.Age == 'From 20 to 29')&(df.Annual_Income=='Less than RM25,000'),:]
df3
```

```
[93]:
```

	Timestamp	Gender	Age	Occupation	\
0	2019/10/01 12:38:43 PM GMT+8	Female	From 20 to 29	Student	
1	2019/10/01 12:38:54 PM GMT+8	Female	From 20 to 29	Student	
3	2019/10/01 12:39:08 PM GMT+8	Female	From 20 to 29	Student	
5	2019/10/01 12:39:39 PM GMT+8	Female	From 20 to 29	Student	
6	2019/10/01 12:39:42 PM GMT+8	Female	From 20 to 29	Student	
8	2019/10/01 12:42:27 PM GMT+8	Female	From 20 to 29	Student	
10	2019/10/01 12:47:00 PM GMT+8	Female	From 20 to 29	Student	
11	2019/10/01 12:48:26 PM GMT+8	Female	From 20 to 29	Student	
12	2019/10/01 12:49:25 PM GMT+8	Female	From 20 to 29	Student	
13	2019/10/01 12:53:09 PM GMT+8	Female	From 20 to 29	Student	
14	2019/10/01 12:53:16 PM GMT+8	Female	From 20 to 29	Student	
23	2019/10/01 1:24:04 PM GMT+8	Female	From 20 to 29	Student	
35	2019/10/01 1:51:56 PM GMT+8	Female	From 20 to 29	Student	
59	2019/10/01 6:19:46 PM GMT+8	Female	From 20 to 29	Student	
65	2019/10/02 7:15:27 PM GMT+8	Female	From 20 to 29	Student	
78	2019/10/03 7:19:36 AM GMT+8	Female	From 20 to 29	Student	

	Annual_Income	Visit_Frequency	Service_preferred	\
0	Less than RM25,000	Rarely	Dine in	
1	Less than RM25,000	Rarely	Take away	
3	Less than RM25,000	Rarely	Take away	
5	Less than RM25,000	Rarely	Dine in	
6	Less than RM25,000	Rarely	Dine in	
8	Less than RM25,000	Rarely	Drive-thru	
10	Less than RM25,000	Rarely	Dine in	
11	Less than RM25,000	Rarely	Dine in	
12	Less than RM25,000	Weekly	Take away	
13	Less than RM25,000	Rarely	Take away	
14	Less than RM25,000	Rarely	Take away	
23	Less than RM25,000	Monthly	Drive-thru	
35	Less than RM25,000	Rarely	Take away	
59	Less than RM25,000	Rarely	Drive-thru	
65	Less than RM25,000	Rarely	Dine in	
78	Less than RM25,000	Rarely	Take away	

	Time_Spent_Frequency	Nearest_Store_Distance	Membership	...	\
0	Between 30 minutes to 1 hour	within 1km	Yes	...	
1	Below 30 minutes	1km - 3km	Yes	...	
3	Below 30 minutes	more than 3km	No	...	
5	Between 30 minutes to 1 hour	more than 3km	No	...	
6	Below 30 minutes	within 1km	Yes	...	
8	Below 30 minutes	more than 3km	Yes	...	
10	Below 30 minutes	more than 3km	No	...	
11	Between 30 minutes to 1 hour	more than 3km	No	...	
12	Below 30 minutes	1km - 3km	Yes	...	
13	Below 30 minutes	1km - 3km	Yes	...	
14	Below 30 minutes	within 1km	Yes	...	
23	Between 1 hour to 2 hours	1km - 3km	Yes	...	
35	Below 30 minutes	more than 3km	No	...	
59	Below 30 minutes	more than 3km	No	...	
65	Between 30 minutes to 1 hour	1km - 3km	No	...	
78	Below 30 minutes	more than 3km	No	...	

	Quality_Rating_vs_Other_Brands	Price_Rating	Sales_Promotion_Importance	...	\
0	4	3	5		
1	4	3	4		
3	2	1	4		
5	4	3	5		
6	5	5	5		
8	5	4	4		
10	4	1	4		
11	3	2	4		
12	4	3	2		
13	4	3	4		
14	5	2	5		
23	5	4	4		
35	4	2	4		
59	4	3	4		
65	4	3	2		
78	2	1	5		

	Ambiance_Rating	WiFi_Rating	Service_Rating	Meetings_hangouts_preference	...	\
0	5	4	4	3		
1	4	4	5	2		
3	3	3	3	3		
5	5	4	5	4		
6	5	3	5	5		
8	4	4	4	4		
10	5	3	3	4		
11	4	3	4	4		
12	4	4	3	4		
13	4	4	4	3		

14	5	5	5	2
23	5	4	4	3
35	4	3	4	1
59	4	3	4	3
65	4	3	4	4
78	2	2	2	2

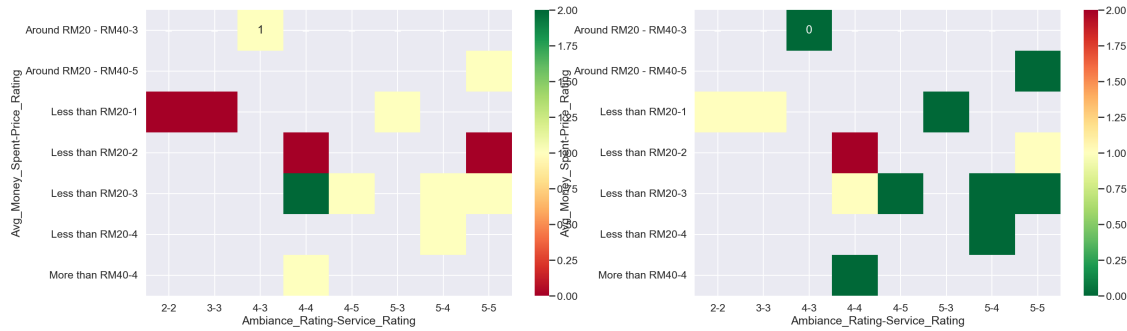
	Promotion_Source	Loyalty	Loyalty_invert
0	Starbucks Website/Apps;Social Media;Emails;Dea...	1	0
1	Social Media;In Store displays	1	0
3	Through friends and word of mouth	0	1
5	Social Media	1	0
6	Starbucks Website/Apps;Social Media	1	0
8	Starbucks Website/Apps;Social Media;Through fr...	1	0
10	Social Media	1	0
11	Starbucks Website/Apps;Social Media;Through fr...	0	1
12	Social Media	1	0
13	Social Media	1	0
14	Social Media;Through friends and word of mouth...	0	1
23	Social Media;Through friends and word of mouth	1	0
35	Social Media	0	1
59	Starbucks Website/Apps;Social Media	1	0
65	Through friends and word of mouth	0	1
78	Social Media;Through friends and word of mouth	0	1

[16 rows x 22 columns]

AvgMoneySpent_vs_PriceRating_vs_AmbianceRating_vs_ServiceRating_vs_Loyalty of the above category

```
[94]: pivot_df = pd.pivot_table(data=df3, index=['Avg_Money_Spent','Price_Rating'],
    ↳columns=['Ambiance_Rating','Service_Rating'], values='Loyalty',
    ↳aggfunc='sum')

plt.figure(figsize=(28,8))
plt.subplot(1,2,1)
sns.heatmap(data=pivot_df, cmap='RdYlGn', annot=True)
pivot_df = pd.pivot_table(data=df3, index=['Avg_Money_Spent','Price_Rating'],
    ↳columns=['Ambiance_Rating','Service_Rating'], values='Loyalty_invert',
    ↳aggfunc='sum')
plt.subplot(1,2,2)
sns.heatmap(data=pivot_df, cmap='RdYlGn_r', annot=True)
plt.show()
```



- customer with ambiance and service rating between 3 -5 are more loyal
- customers with less price rating are less loyal

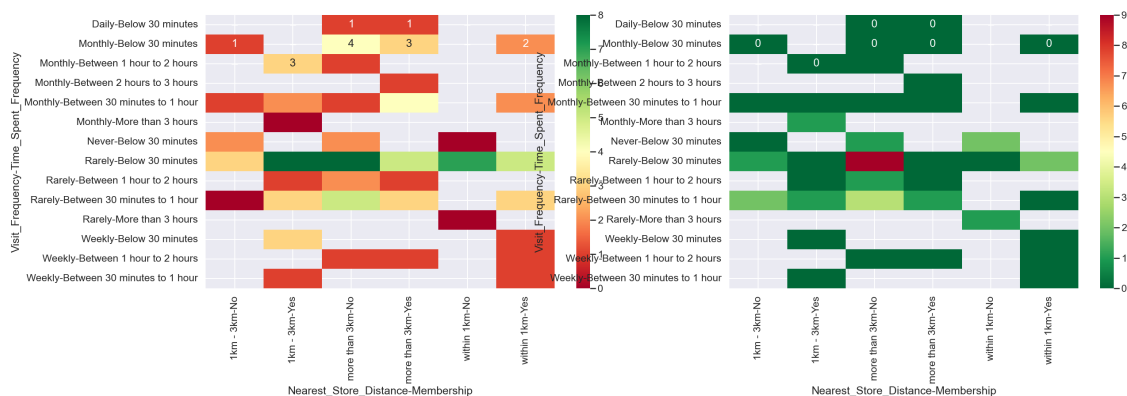
VisitFrequency_vs_TimeSpentFrequency_vs_NearestStoreDistance_vs_Membership_vs_Loyalty

```
[95]: pivot_df = pd.pivot_table(data=df,
    ↪ index=['Visit_Frequency', 'Time_Spent_Frequency'],
    ↪ columns=['Nearest_Store_Distance', 'Membership'], values='Loyalty',
    ↪ aggfunc='sum')

plt.figure(figsize=(28,8))
plt.subplot(1,2,1)
sns.heatmap(data=pivot_df, cmap='RdYlGn', annot=True)

pivot_df = pd.pivot_table(data=df,
    ↪ index=['Visit_Frequency', 'Time_Spent_Frequency'],
    ↪ columns=['Nearest_Store_Distance', 'Membership'], values='Loyalty_invert',
    ↪ aggfunc='sum')

plt.subplot(1,2,2)
sns.heatmap(data=pivot_df, cmap='RdYlGn_r', annot=True)
plt.show()
```



- It is evident that customers having membership are more loyal compared to customers without

membership

- Customers visiting rarely, time_spent_frequency below 30min, nearest store more than 3km and doesn't have membership, they have almost equal positive and negative responses. whereas nearest store 1km-3km and have membership, they are positively responding
- Weekly visiting customers are very low but stores within 1km they are positively responding
- The green color in the 2nd graph says we don't have much negative responses. Whereas the red color in the 1st graph says we don't have more positive responses as well. Only few group of customers are exhibiting high positive responses which is evident
- Both customers with visiting daily spending 30 mins and monthly visiting customers are all loyal except one with time spending more than 3 hours.

Lets analyse the data for the category with most non-loyal customers (9) in the above graph

```
[96]: df2 = df.loc[(df.Visit_Frequency== 'Rarely')&(df.Time_Spent_Frequency == 'Below_
↳30 minutes') & (df.Nearest_Store_Distance == 'more than 3km')&(df.
↳Membership=='No'),:]
```

```
[97]: pd.set_option('display.max_columns', 50)
df2
```

```
[97]:
```

	Timestamp	Gender	Age	Occupation \
3	2019/10/01 12:39:08 PM GMT+8	Female	From 20 to 29	Student
10	2019/10/01 12:47:00 PM GMT+8	Female	From 20 to 29	Student
32	2019/10/01 1:45:12 PM GMT+8	Female	From 30 to 39	Employed
35	2019/10/01 1:51:56 PM GMT+8	Female	From 20 to 29	Student
51	2019/10/01 3:16:32 PM GMT+8	Female	Below 20	Student
53	2019/10/01 3:21:16 PM GMT+8	Female	Below 20	Student
59	2019/10/01 6:19:46 PM GMT+8	Female	From 20 to 29	Student
64	2019/10/02 7:15:13 PM GMT+8	Female	From 20 to 29	Employed
68	2019/10/02 7:29:53 PM GMT+8	Female	From 20 to 29	Employed
74	2019/10/02 8:31:21 PM GMT+8	Female	From 20 to 29	Housewife
78	2019/10/03 7:19:36 AM GMT+8	Female	From 20 to 29	Student
79	2019/10/03 7:21:08 AM GMT+8	Female	Below 20	Student
96	2019/10/03 3:44:13 PM GMT+8	Female	From 20 to 29	Self-employed
106	2019/10/03 6:46:53 PM GMT+8	Male	From 20 to 29	Student
109	2019/10/03 7:40:31 PM GMT+8	Male	From 20 to 29	Student
110	2019/10/03 7:43:00 PM GMT+8	Male	From 20 to 29	Student
113	2019/10/03 8:58:26 PM GMT+8	Female	Below 20	Student

	Annual_Income	Visit_Frequency	Service_preferred \
3	Less than RM25,000	Rarely	Take away
10	Less than RM25,000	Rarely	Dine in
32	RM25,000 - RM50,000	Rarely	Take away
35	Less than RM25,000	Rarely	Take away
51	Less than RM25,000	Rarely	Dine in
53	Less than RM25,000	Rarely	Drive-thru
59	Less than RM25,000	Rarely	Drive-thru
64	Less than RM25,000	Rarely	Take away

68	Less than RM25,000	Rarely	Dine in
74	RM50,000 - RM100,000	Rarely	Drive-thru
78	Less than RM25,000	Rarely	Take away
79	Less than RM25,000	Rarely	Take away
96	Less than RM25,000	Rarely	Take away
106	Less than RM25,000	Rarely	Take away
109	Less than RM25,000	Rarely	Dine in
110	Less than RM25,000	Rarely	Take away
113	Less than RM25,000	Rarely	Take away

	Time_Spent_Frequency	Nearest_Store_Distance	Membership \
3	Below 30 minutes	more than 3km	No
10	Below 30 minutes	more than 3km	No
32	Below 30 minutes	more than 3km	No
35	Below 30 minutes	more than 3km	No
51	Below 30 minutes	more than 3km	No
53	Below 30 minutes	more than 3km	No
59	Below 30 minutes	more than 3km	No
64	Below 30 minutes	more than 3km	No
68	Below 30 minutes	more than 3km	No
74	Below 30 minutes	more than 3km	No
78	Below 30 minutes	more than 3km	No
79	Below 30 minutes	more than 3km	No
96	Below 30 minutes	more than 3km	No
106	Below 30 minutes	more than 3km	No
109	Below 30 minutes	more than 3km	No
110	Below 30 minutes	more than 3km	No
113	Below 30 minutes	more than 3km	No

	Frequent_Product	Avg_Money_Spent	Quality_Rating_vs_Other_Brands \
3	Coffee	Less than RM20	2
10	Cold drinks	Less than RM20	4
32	Coffee	Around RM20 - RM40	2
35	Coffee	Less than RM20	4
51	Cold drinks	Less than RM20	3
53	Coffee	Around RM20 - RM40	3
59	Cold drinks	Less than RM20	4
64	Coffee	Zero	3
68	Coffee	Zero	2
74	Coffee;Cold drinks	Around RM20 - RM40	3
78	Coffee	Less than RM20	2
79	Cold drinks	Less than RM20	2
96	Cold drinks	Less than RM20	3
106	Coffee	Around RM20 - RM40	3
109	Coffee;Pastries	Less than RM20	3
110	Cold drinks	Zero	4
113	Cold drinks	Less than RM20	3

	Price_Rating	Sales_Promotion_Importance	Ambiance_Rating	WiFi_Rating	\
3	1		4	3	3
10	1		4	5	3
32	3		5	5	3
35	2		4	4	3
51	3		2	2	2
53	3		2	3	3
59	3		4	4	3
64	1		5	3	4
68	1		5	4	4
74	2		3	3	3
78	1		5	2	2
79	2		3	2	2
96	3		1	4	3
106	3		3	3	3
109	3		3	3	3
110	2		3	5	4
113	4		5	5	5

	Service_Rating	Meetings_hangouts_preference	\
3	3		3
10	3		4
32	5		5
35	4		1
51	4		3
53	3		3
59	4		3
64	4		5
68	4		1
74	5		4
78	2		2
79	2		2
96	4		4
106	3		3
109	3		2
110	4		2
113	4		4

	Promotion_Source	Loyalty	\
3	Through friends and word of mouth	0	
10	Social Media	1	
32	Social Media	1	
35	Social Media	0	
51	Social Media;Through friends and word of mouth	0	
53	Social Media	1	
59	Starbucks Website/Apps;Social Media	1	

64	Social Media	0
68	Starbucks Website/Apps;Social Media;Through fr...	0
74	Social Media	1
78	Social Media;Through friends and word of mouth	0
79	Social Media;Deal sites (fave, iprice, etc...)	0
96	Social Media;Through friends and word of mouth	1
106	Starbucks Website/Apps;Social Media	1
109	Social Media	0
110	Social Media	0
113	Social Media	1

	Loyalty_invert
3	1
10	0
32	0
35	1
51	1
53	0
59	0
64	1
68	1
74	0
78	1
79	1
96	0
106	0
109	1
110	1
113	0

- majority of the customers are Female
- the customers visit frequency is Rare
- Time spent frequency below 30mins
- Nearest store more tha 3km
- The customers don't have membership

AvgMoneySpent_vs_PriceRating_vs_AmbianceRating_vs_ServiceRating_vs_Loyalty for above category

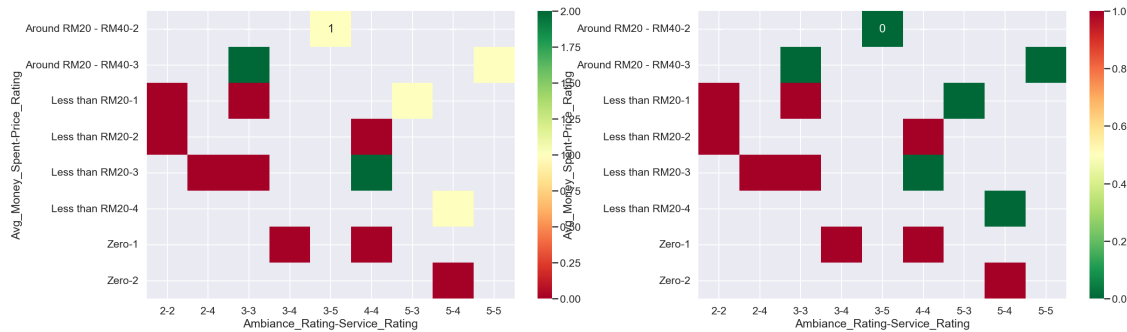
```
[98]: pivot_df = pd.pivot_table(data=df2, index=['Avg_Money_Spent','Price_Rating'],
    ↳columns=['Ambiance_Rating','Service_Rating'], values='Loyalty',
    ↳aggfunc='sum')

plt.figure(figsize=(28,8))
plt.subplot(1,2,1)
sns.heatmap(data=pivot_df, cmap='RdYlGn', annot=True)
```

```

pivot_df = pd.pivot_table(data=df2, index=['Avg_Money_Spent','Price_Rating'],
    columns=['Ambiance_Rating','Service_Rating'], values='Loyalty_invert',
    aggfunc='sum')
plt.subplot(1,2,2)
sns.heatmap(data=pivot_df, cmap='RdYlGn_r', annot=True)
plt.show()

```



- Customers with Price_rating 1 or 2 are not loyal even the ambiance and Service rating is ≥ 3
- customer with Price_rating > 3 are more loyal and the ambiance and Service rating with high rating has positive impact

Lets understand these features impact on complete data

```

[99]: df3 = df.loc[(df.Visit_Frequency== 'Daily')|(df.Visit_Frequency== 'Monthly'),:]
df3

```

```

[99]:
Timestamp      Gender  Age      Occupation \
2   2019/10/01 12:38:56 PM GMT+8    Male  From 20 to 29    Employed
4   2019/10/01 12:39:20 PM GMT+8    Male  From 20 to 29    Student
9   2019/10/01 12:43:36 PM GMT+8    Male  From 20 to 29    Employed
16  2019/10/01 12:59:11 PM GMT+8    Male  From 30 to 39    Employed
23  2019/10/01 1:24:04 PM GMT+8   Female  From 20 to 29    Student
25  2019/10/01 1:25:56 PM GMT+8    Male  From 30 to 39    Employed
27  2019/10/01 1:33:54 PM GMT+8    Male  From 20 to 29  Self-employed
30  2019/10/01 1:39:16 PM GMT+8   Female  From 20 to 29    Employed
41  2019/10/01 2:06:24 PM GMT+8    Male  From 20 to 29    Employed
43  2019/10/01 2:35:40 PM GMT+8   Female  From 20 to 29    Employed
52  2019/10/01 3:20:55 PM GMT+8   Female    40 and above  Housewife
55  2019/10/01 4:02:35 PM GMT+8   Female  From 20 to 29    Employed
57  2019/10/01 4:03:57 PM GMT+8    Male    Below 20    Student
58  2019/10/01 4:05:59 PM GMT+8    Male    Below 20    Student
66  2019/10/02 7:23:55 PM GMT+8   Female  From 20 to 29  Self-employed
72  2019/10/02 8:08:37 PM GMT+8   Female  From 20 to 29    Employed
77  2019/10/02 9:19:50 PM GMT+8    Male  From 20 to 29    Employed

```

80	2019/10/03 8:46:25 AM GMT+8	Female	From 20 to 29	Employed
85	2019/10/03 11:17:27 AM GMT+8	Male	From 30 to 39	Self-employed
91	2019/10/03 12:13:56 PM GMT+8	Female	From 30 to 39	Employed
94	2019/10/03 2:34:09 PM GMT+8	Male	From 20 to 29	Employed
102	2019/10/03 6:35:21 PM GMT+8	Male	From 20 to 29	Self-employed
105	2019/10/03 6:45:28 PM GMT+8	Male	40 and above	Employed
111	2019/10/03 7:47:00 PM GMT+8	Female	From 20 to 29	Employed
115	2019/10/03 10:38:42 PM GMT+8	Male	Below 20	Student
116	2019/10/03 11:24:55 PM GMT+8	Male	From 30 to 39	Student
117	2019/10/04 12:24:26 AM GMT+8	Male	40 and above	Self-employed
118	2019/10/04 9:30:09 AM GMT+8	Male	From 20 to 29	Employed

	Annual_Income	Visit_Frequency	Service_preferred \
2	Less than RM25,000	Monthly	Dine in
4	Less than RM25,000	Monthly	Take away
9	Less than RM25,000	Monthly	Take away
16	RM50,000 - RM100,000	Monthly	Drive-thru
23	Less than RM25,000	Monthly	Drive-thru
25	More than RM150,000	Monthly	Dine in
27	Less than RM25,000	Monthly	Take away
30	RM25,000 - RM50,000	Monthly	Take away
41	Less than RM25,000	Monthly	Dine in
43	Less than RM25,000	Monthly	Take away
52	Less than RM25,000	Monthly	Take away
55	RM25,000 - RM50,000	Monthly	Take away
57	Less than RM25,000	Monthly	Dine in
58	Less than RM25,000	Monthly	Dine in
66	RM25,000 - RM50,000	Monthly	Dine in
72	Less than RM25,000	Monthly	Take away
77	RM50,000 - RM100,000	Monthly	Dine in
80	RM50,000 - RM100,000	Monthly	Drive-thru
85	More than RM150,000	Monthly	Dine in
91	RM25,000 - RM50,000	Monthly	Take away
94	RM50,000 - RM100,000	Monthly	Take away
102	RM50,000 - RM100,000	Daily	Drive-thru
105	RM50,000 - RM100,000	Monthly	Drive-thru
111	Less than RM25,000	Monthly	Take away
115	Less than RM25,000	Daily	Take away
116	Less than RM25,000	Monthly	Dine in
117	RM25,000 - RM50,000	Monthly	Dine in
118	Less than RM25,000	Monthly	Dine in

	Time_Spent_Frequency	Nearest_Store_Distance	Membership \
2	Between 30 minutes to 1 hour	more than 3km	Yes
4	Between 30 minutes to 1 hour	1km - 3km	No
9	Below 30 minutes	more than 3km	No
16	Below 30 minutes	within 1km	Yes

23	Between 1 hour to 2 hours	1km - 3km	Yes
25	Between 30 minutes to 1 hour	1km - 3km	Yes
27	Below 30 minutes	more than 3km	No
30	Between 30 minutes to 1 hour	more than 3km	Yes
41	Between 30 minutes to 1 hour	within 1km	Yes
43	Below 30 minutes	more than 3km	No
52	Below 30 minutes	more than 3km	Yes
55	Between 30 minutes to 1 hour	1km - 3km	Yes
57	Between 30 minutes to 1 hour	more than 3km	Yes
58	Below 30 minutes	1km - 3km	No
66	Below 30 minutes	within 1km	Yes
72	Below 30 minutes	more than 3km	Yes
77	Between 30 minutes to 1 hour	more than 3km	Yes
80	More than 3 hours	1km - 3km	Yes
85	Between 2 hours to 3 hours	more than 3km	Yes
91	Between 30 minutes to 1 hour	within 1km	Yes
94	Below 30 minutes	more than 3km	Yes
102	Below 30 minutes	more than 3km	Yes
105	Between 30 minutes to 1 hour	more than 3km	No
111	Below 30 minutes	more than 3km	No
115	Below 30 minutes	more than 3km	No
116	Between 1 hour to 2 hours	more than 3km	No
117	Between 1 hour to 2 hours	1km - 3km	Yes
118	Between 1 hour to 2 hours	1km - 3km	Yes

	Frequent_Product	Avg_Money_Spent \
2	Coffee	Less than RM20
4	Coffee;Sandwiches	Around RM20 - RM40
9	Coffee	Around RM20 - RM40
16	Coffee	Around RM20 - RM40
23	Cold drinks;Pastries;Sandwiches	Less than RM20
25	Coffee;Cold drinks	Around RM20 - RM40
27	Coffee	Around RM20 - RM40
30	Coffee;Pastries;Sandwiches	Around RM20 - RM40
41	Coffee	Around RM20 - RM40
43	Coffee;Pastries	Around RM20 - RM40
52	Cold drinks;Juices;Pastries	More than RM40
55	Coffee	Less than RM20
57	Coffee	Less than RM20
58	Coffee	Less than RM20
66	Coffee;Cold drinks;Pastries;Sandwiches	Around RM20 - RM40
72	Coffee	Less than RM20
77	Coffee	Around RM20 - RM40
80	Coffee	Around RM20 - RM40
85	Jaws chip	Around RM20 - RM40
91	Coffee;Pastries	Around RM20 - RM40
94	Coffee	Around RM20 - RM40

102	Coffee	Around RM20 - RM40
105	Cold drinks	Around RM20 - RM40
111	Cold drinks	Less than RM20
115	Cold drinks	Around RM20 - RM40
116	Cold drinks	Less than RM20
117	Coffee	Around RM20 - RM40
118	Coffee;Cold drinks;Juices;Pastries;Sandwiches	More than RM40

	Quality_Rating_vs_Other_Brands	Price_Rating	Sales_Promotion_Importance	\
2	4	3	4	
4	3	3	4	
9	4	3	3	
16	4	3	3	
23	5	4	4	
25	4	3	1	
27	5	3	4	
30	3	1	4	
41	5	4	5	
43	4	4	5	
52	5	4	3	
55	4	3	4	
57	5	5	5	
58	3	3	3	
66	4	3	4	
72	4	2	4	
77	4	2	1	
80	3	2	4	
85	4	3	4	
91	4	3	4	
94	3	1	3	
102	4	2	4	
105	4	3	5	
111	5	4	4	
115	5	5	5	
116	4	4	5	
117	3	3	5	
118	5	5	5	

	Ambiance_Rating	WiFi_Rating	Service_Rating	Meetings_hangouts_preference	\
2	4	4	4	3	
4	2	2	3	3	
9	4	3	3	4	
16	4	3	3	3	
23	5	4	4	3	
25	4	4	5	4	
27	4	3	4	3	
30	4	3	4	4	

41	5	3	5	5
43	4	4	5	5
52	5	3	5	5
55	3	2	3	4
57	5	5	5	5
58	3	4	3	3
66	5	4	4	4
72	4	3	4	3
77	4	1	4	4
80	3	1	3	3
85	4	3	4	4
91	5	5	4	5
94	3	1	3	2
102	4	3	3	3
105	4	4	4	4
111	4	4	4	4
115	5	5	5	5
116	4	2	3	4
117	3	2	4	4
118	5	5	5	5

	Promotion_Source	Loyalty \
2	In Store displays;Billboards	1
4	Starbucks Website/Apps;Social Media	1
9	Social Media;Through friends and word of mouth	1
16	Social Media	1
23	Social Media;Through friends and word of mouth	1
25	Social Media;In Store displays;Billboards	1
27	Social Media	1
30	Starbucks Website/Apps;Social Media;Emails;Thr...	1
41	Starbucks Website/Apps;Social Media	1
43	Starbucks Website/Apps;Social Media;Emails;Bil...	1
52	Starbucks Website/Apps;Social Media;Deal sites...	1
55	Starbucks Website/Apps	1
57	Through friends and word of mouth	1
58	Social Media	1
66	Starbucks Website/Apps;Social Media;Emails;Thr...	1
72	Through friends and word of mouth	1
77	Social Media	1
80	Starbucks Website/Apps	0
85	Starbucks Website/Apps;Emails	1
91	Starbucks Website/Apps;Social Media;Emails;Thr...	1
94	Social Media;Through friends and word of mouth	1
102	Social Media;Emails	1
105	Starbucks Website/Apps	1
111	Social Media;Through friends and word of mouth...	1
115	Social Media;Through friends and word of mouth	1

116	Social Media	1
117	Starbucks Website/Apps;Social Media	1
118	Starbucks Website/Apps;Social Media;Emails;Dea...	1

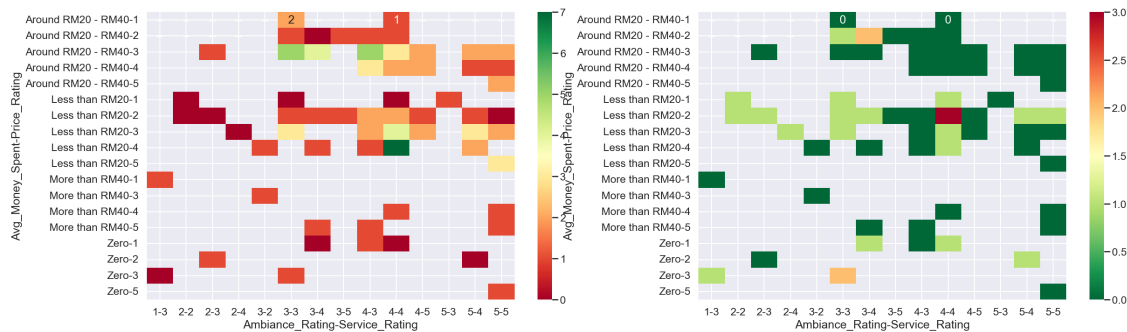
	Loyalty_invert
2	0
4	0
9	0
16	0
23	0
25	0
27	0
30	0
41	0
43	0
52	0
55	0
57	0
58	0
66	0
72	0
77	0
80	1
85	0
91	0
94	0
102	0
105	0
111	0
115	0
116	0
117	0
118	0

AvgMoneySpent_vs_PriceRating_vs_AmbianceRating_vs_ServiceRating_vs_Loyalty

```
[100]: pivot_df = pd.pivot_table(data=df, index=['Avg_Money_Spent', 'Price_Rating'],
    ↪columns=['Ambiance_Rating', 'Service_Rating'], values='Loyalty',
    ↪aggfunc='sum')

plt.figure(figsize=(28,8))
plt.subplot(1,2,1)
sns.heatmap(data=pivot_df, cmap='RdYlGn', annot=True)
pivot_df = pd.pivot_table(data=df, index=['Avg_Money_Spent', 'Price_Rating'],
    ↪columns=['Ambiance_Rating', 'Service_Rating'], values='Loyalty_invert',
    ↪aggfunc='sum')
plt.subplot(1,2,2)
```

```
sns.heatmap(data=pivot_df, cmap='RdYlGn_r', annot=True)
plt.show()
```



- Loyalty increasing with the increase in Price rating, ambiance rating, service rating
- Customer giving high ambiance rating, Service rating are more loyal if the average money spent greater than RM20. Price rating doesn't have much impact on this. These are customers who are more interested in Services and ambiance

Create a temp feature to calculate the categories count for the chi-square test

```
[101]: df['temp'] = 1
df.temp
```

```
[101]: 0      1
      1      1
      2      1
      3      1
      4      1
      ..
     116      1
     117      1
     118      1
     119      1
     120      1
      Name: temp, Length: 119, dtype: int64
```

```
[102]: def chiSquareTest(df, col1, col2, col_list):
        cont_table = df.groupby([col1, col2])['temp'].count().unstack()
        cont_table.fillna(0, inplace=True)
        stat, p, dof, expected = st.chi2_contingency(cont_table)

        prob = 0.90
        critical = st.chi2.ppf(prob, dof)
        if abs(stat) >= critical:
            print('Dependent (reject H0) and the features are: ' + col1)
            print(stat, critical)
```



```
col_list.append(col1)
```

```
[103]: cols = df.columns
```

```
[104]: col_list = []  
for i in cols[1:-4]:  
    #print("Correlation of Col: "+i)  
    chiSquareTest(df, i, 'Loyalty', col_list)
```

```
Dependent (reject H0) and the features are: Visit_Frequency  
11.76312078559738 7.779440339734858  
Dependent (reject H0) and the features are: Time_Spent_Frequency  
8.949119650202958 7.779440339734858  
Dependent (reject H0) and the features are: Membership  
10.225935779540809 2.705543454095404  
Dependent (reject H0) and the features are: Avg_Money_Spent  
18.313651362448674 6.251388631170325  
Dependent (reject H0) and the features are: Quality_Rating_vs_Other_Brands  
17.992995327213645 6.251388631170325  
Dependent (reject H0) and the features are: Price_Rating  
24.535001253671467 7.779440339734858  
Dependent (reject H0) and the features are: Ambiance_Rating  
13.032220403709768 7.779440339734858  
Dependent (reject H0) and the features are: Service_Rating  
7.203973586636884 6.251388631170325  
Dependent (reject H0) and the features are: Meetings_hangouts_preference  
14.929696630357324 7.779440339734858
```

The columns with significant difference with the loyalty

```
[105]: print(col_list)
```

```
['Visit_Frequency', 'Time_Spent_Frequency', 'Membership', 'Avg_Money_Spent',  
'Quality_Rating_vs_Other_Brands', 'Price_Rating', 'Ambiance_Rating',  
'Service_Rating', 'Meetings_hangouts_preference']
```

Found different categories among loyal and non-loyal customers. As the number of customers belonging to those categories are very less, need more data to understand their behaviour stability.