Great

Learning

&

UT Austin

Prediction whether the customer is going to adopt the tourism package based on a social media campaign.

Social Media_Tourism_Project

Project Notes-1

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GO-GO AIR

Effectiveness of Social Media Campaign for higher revenue through an increase in sales of tickets

Image downloaded from internet

1. INTRODUCTION OF THE BUSINESS PROBLEM

a) <u>Defining problem statement</u>

Go-Go AIR is a multinational aviation organization headquartered in Mumbai, known for its world class services. Due to huge customer obsession, the organization believes in continues learning and improvement. The management is keen on understanding and removing the flaws across all the departments. Based on feedback, it was understood that the name of the brand Go-Go AIR is degrading significantly due to the frequent cold calls to the masses. Traditionally, the marketing and sales functions relied on reaching out to the potential customers through the conventional method of cold calling. But Team Go-Go AIR has realized that this practice isn't relevant anymore. In order to replace it, various strategies were suggested to the management.

Finally, the esteemed Marketing and Sales Department came up with the idea of reaching out to the masses using social media marketing campaigns. It was eventually approved by management. Hence Go-Go Air decided to collaborate with a social media platform for Ad campaigns.

b) Need of the study

The social media ad campaigns attract a huge cost per customer acquisition. Therefore, a pilot project was conducted where the social media ad was displayed to the audience and the data was collected. Based on the data, the management aims to understand digital and social behavior of existing customers. They instructed the Marketing Information System (MIS) team, to come up with a model which will predict that customer will buy the ticket or not.

c) Understanding business opportunity

The aim of this activity is to achieve an increase in sales revenue by at least 30% in the upcoming financial year through the social media ad campaigns and cost cutting by ending tele calling processes by 50%.

Eventually the MIS team agreed to build a model using machine learning algorithms. They were also asked to check the performance of model on the real data & then recommend deployment. Based on the prediction, the social media ad shall be displayed on the targeted customers.

“

Brands that ignore social media…will die. It’s that simple

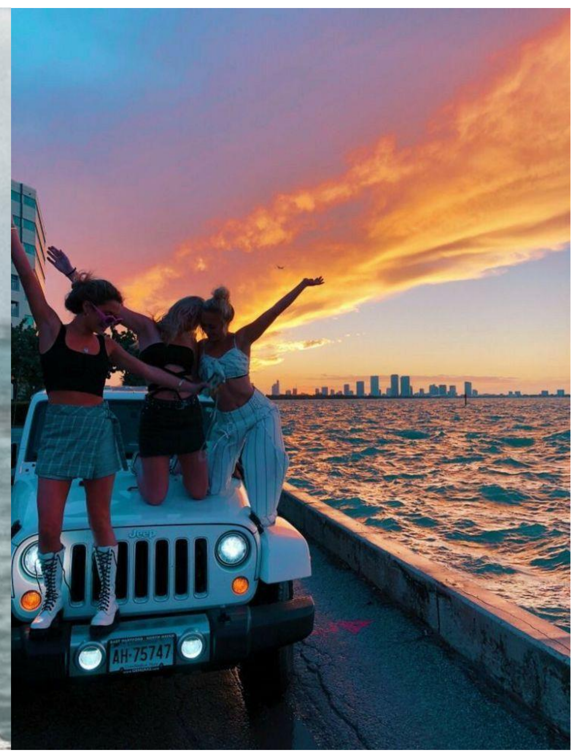
-Jeff Ragovin

”

SOCIAL MEDIA & Ad Campaigns

According to Wikipedia, **Social media** are interactive technologies that allow the creation or sharing/exchange of information, ideas, interests, and other forms of expression via virtual communities and networks citation. Example Facebook, Twitter, Instagram etc.

A social media campaign is a coordinated marketing designed to reinforce information or sentiments —about a product, service, or overall brand—through at least one social media platform.



Images used for representation

2. DATA REPORT

The data was shared with the MIS team. Initially, the data extracted was saved in an MS Excel file and shared. The file was then converted to CSV file so that it can be uploaded into Python 3 Jupyter Notebook for analysis, visualization and model building.

a) <u>Understanding how data was collected in terms of time, frequency and methodology</u>
All the necessary libraries were used and the data CSV file was uploaded for the analysis Also, we can understand from features like 'Yearly_avg_view_on_travel_page', 'yearly_avg_Outstation_checkins', 'Yearly_avg_comment_on_travel_page' etc., the data was collected over a time period of several years. However, from features like 'Daily_Avg_mins_spend_on_traveling_page', we can understand the frequency, that the data was captured daily from the social media account of the users. Also, the data has several variables like 'member_in_family', 'week_since_last_outstation_checkin' which is the information filled by the customer in the info section of social media website.

b) <u>Visual inspection of data</u>
After uploading the data, it was understood that the number of data points or the rows were 11760 and number of features or variables were 17.
This gives the understanding that this data has information of 11760 customers.
In the figure below we can see initial 10 data points. We can see that there are Null (NaN) values in the data.

	0	1	2	3	4	5	6	7	8	9
UserID	1000001	1000002	1000003	1000004	1000005	1000006	1000007	1000008	1000009	1000010
Taken_product	Yes	No	Yes	No	No	No	No	No	No	No
Yearly_avg_view_on_travel_page	307.0	367.0	277.0	247.0	202.0	240.0	NaN	225.0	285.0	270.0
preferred_device	iOS and Android	iOS	iOS and Android	iOS	iOS and Android	iOS	iOS and Android	iOS and Android	iOS	iOS and Android
total_likes_on_outstation_checkin_given	38570.0	9765.0	48055.0	48720.0	20685.0	35175.0	46340.0	NaN	7560.0	45465.0
yearly_avg_Outstation_checkins	1	1	1	1	1	1	1	24	23	27
member_in_family	2	1	2	4	1	2	Three	1	3	3
preferred_location_type	Financial	Financial	Other	Financial	Medical	Financial	Medical	Financial	Financial	NaN
Yearly_avg_comment_on_travel_page	94.0	61.0	92.0	56.0	40.0	79.0	81.0	67.0	44.0	94.0
total_likes_on_outofstation_checkin_received	5993	5130	2090	2909	3468	3068	2670	2693	9526	5237
week_since_last_outstation_checkin	8	1	6	1	9	0	4	1	0	6
following_company_page	Yes	No	Yes	Yes	No	No	Yes	No	No	No
montly_avg_comment_on_company_page	11	23	15	11	12	13	20	22	21	13
working_flag	No	Yes	No	No	No	No	Yes	Yes	Yes	No
travelling_network_rating	1	4	2	3	4	3	1	2	2	2
Adult_flag	0	1	0	0	1	0	3	1	0	2
Daily_Avg_mins_spend_on_traveling_page	8	10	7	8	6	8	12	1	10	17

From the below table we can understand the nature of data whether it is categorical or numeric in nature.

S. No.	Feature Name	Data Type
1	UserID	
2	Taken_product	Categorical
3	Yearly_avg_view_on_travel_page	Numeric
4	preferred_device	Categorical
5	total_likes_on_outstation_checkin_given	Numeric
6	yearly_avg_Outstation_checkins	Numeric
7	member_in_family	Numeric
8	preferred_location_type	Categorical
9	Yearly_avg_comment_on_travel_page	Numeric
10	total_likes_on_outofstation_checkin_received	Numeric
11	week_since_last_outstation_checkin	Numeric
12	following_company_page	Categorical
13	montly_avg_comment_on_company_page	Numeric
14	working_flag	Categorical
15	travelling_network_rating	Categorical
16	Adult_flag	Categorical
17	Daily_Avg_mins_spend_on_traveling_page	Numeric

Also, below are the descriptive details of the data. From count we can understand that there are several null values in numeric variables. Here, we won't be able to infere much about data.

In variable 'Adult_flag', we can see that the maximum value is 3. This is not valid as it's categorical in nature. It can yes or no, either 0 or 1.

	count	mean	std	min	25%	50%	75%	max
UserID	11760.0	1.005880e+06	3394.963917	1000001.0	1002940.75	1005880.5	1008820.25	1011760.0
Yearly_avg_view_on_travel_page	11179.0	2.808308e+02	68.182958	35.0	232.00	271.0	324.00	464.0
total_likes_on_outstation_checkin_given	11379.0	2.817048e+04	14385.032134	3570.0	16380.00	28076.0	40525.00	252430.0
Yearly_avg_comment_on_travel_page	11554.0	7.479003e+01	24.026650	3.0	57.00	75.0	92.00	815.0
total_likes_on_outofstation_checkin_received	11760.0	6.531699e+03	4706.613785	1009.0	2940.75	4948.0	8393.25	20065.0
week_since_last_outstation_checkin	11760.0	3.203571e+00	2.616365	0.0	1.00	3.0	5.00	11.0
montly_avg_comment_on_company_page	11760.0	2.866156e+01	48.660504	11.0	17.00	22.0	27.00	500.0
travelling_network_rating	11760.0	2.712245e+00	1.080887	1.0	2.00	3.0	4.00	4.0
Adult_flag	11760.0	7.938776e-01	0.851823	0.0	0.00	1.0	1.00	3.0
Daily_Avg_mins_spend_on_traveling_page	11760.0	1.381743e+01	9.070657	0.0	8.00	12.0	18.00	270.0

c) Understanding of attributes
The following is the data dictionary provided for the social media ad campaign database. Along with the description we have mentioned if the remaining is required for any column or not.

Variable	Renaming Required	Description
UserID	No	Unique ID of user
Buy_ticket	No	Buy ticket in next month
Yearly_avg_view_on_travel_page	No	Average yearly views on any travel related page by user
preferred_device	No	Through which device user preferred to do login
total_likes_on_outstation_checkin_given	No	Total number of likes given by a user on out of station checkings in last year
yearly_avg_Outstation_checkins	No	Average number of out of station check-in done by user
member_in_family	No	Total number of relationship mentioned by user in the account
preferred_location_type	No	Preferred type of the location for travelling of user
Yearly_avg_comment_on_travel_page	No	Average yearly comments on any travel related page by user
total_likes_on_outofstation_checkin_received	No	Total number of likes received by a user on out of station checkings in last year
week_since_last_outstation_checkin	No	Number of weeks since last out of station check-in update by user
following_company_page	No	Weather the customer is following company page (Yes or No)
montly_avg_comment_on_company_page	No	Average monthly comments on company page by user
working_flag	No	Weather the customer is working or not
travelling_network_rating	No	Does user have close friends who also like travelling. 1 is highs and 4 is lowest
Adult_flag	No	Weather the customer is adult or not
Daily_Avg_mins_spend_on_traveling_page	No	Average time spend on the company page by user on daily basis

In the below table, we can see that UserID, total_likes_on_outofstation_checkin_received, week_since_last_outstation_checkin, montly_avg_comment_on_company_page, travelling_network_rating, Adult_flag, Daily_Avg_mins_spend_on_traveling_page has variable type 'integer'. The variables 'Yearly_avg_view_on_travel_page', 'total_likes_on_outstation_checkin_given', 'Yearly_avg_comment_on_travel_page' has data type 'float'. The remaining features have data type 'object'.

We can also see that there are several Null values in the features. We shall treat them in the NULL value treatment ahead.

```
RangeIndex: 11760 entries, 0 to 11759
Data columns (total 17 columns):
 #   Column                                      Non-Null Count  Dtype  
---  ------                                      --------------  -----  
 0   UserID                                      11760 non-null  int64  
 1   Taken_product                               11760 non-null  object 
 2   Yearly_avg_view_on_travel_page              11179 non-null  float64
 3   preferred_device                            11707 non-null  object 
 4   total_likes_on_outstation_checkin_given     11379 non-null  float64
 5   yearly_avg_Outstation_checkins              11685 non-null  object 
 6   member_in_family                            11760 non-null  object 
 7   preferred_location_type                     11729 non-null  object 
 8   Yearly_avg_comment_on_travel_page           11554 non-null  float64
 9   total_likes_on_outofstation_checkin_received  11760 non-null  int64  
 10  week_since_last_outstation_checkin          11760 non-null  int64  
 11  following_company_page                      11657 non-null  object 
 12  montly_avg_comment_on_company_page          11760 non-null  int64  
 13  working_flag                                11760 non-null  object 
 14  travelling_network_rating                   11760 non-null  int64  
 15  Adult_flag                                  11760 non-null  int64  
 16  Daily_Avg_mins_spend_on_traveling_page      11760 non-null  int64  
dtypes: float64(3), int64(7), object(7)
```

From the data we can also understand that yearly average view on travel page is 280 for a user.

The percentage of Users buying ticket is 16.12. The percentage of Users not buying ticket is 83.88.

```
No     9864
Yes    1896
Name: Taken_product, dtype: int64
```

3. EXPLORATORY DATA ANALYSIS

a) Univariate Analysis

All the unique values and the frequency of the occurrence of any data point in the entire dataset were done.

Below are the findings:

1. UserID

```
[1000001 1000002 1000003 ... 1011758 1011759 1011760]
1000001    1
1007834    1
1007836    1
1007837    1
1007838    1
          ..
1003922    1
1003923    1
1003924    1
1003925    1
1011760    1
Name: UserID, Length: 11760, dtype: int64
```

Here we have all 11760 unique user IDs. This does not require any treatment.

2. Taken_product

```
['Yes' 'No']
No     9864
Yes    1896
Name: Taken_product, dtype: int64
```

The number of people who has opted to take the product are ‘yes’ and people not buying the product are labelled as ‘no’.

3. Yearly_avg_view_on_travel_page

```
262.0    190
255.0    186
270.0    179
217.0    165
232.0    160
        ...
149.0      2
464.0      1
146.0      1
458.0      1
463.0      1
Name: Yearly_avg_view_on_travel_page, Length: 331, dtype: int64
```

It is yearly average view of every user on the social media page.

4. Preferred Device

```
['iOS and Android' 'iOS' 'ANDROID' nan 'Android' 'Android OS' 'Other'
 'Others' 'Tab' 'Laptop' 'Mobile']
Tab                 4172
iOS and Android     4134
Laptop              1108
iOS                 1095
Mobile               600
Android              315
Android OS           145
ANDROID              134
Other                  2
Others                 2
Name: preferred_device, dtype: int64
```

In the column 'preferred_device', the attributes 'Andriod' and 'ANDRIOD' are same but the only difference is of case lower and upper. The attributes 'Other' and 'Others' are also same therefore they were transformed.

5. total_likes_on_outstation_checkin_given

```
[38570.  9765. 48055. ...  5478. 35851. 22025.]
24185.0    12
11515.0    11
18550.0    10
37870.0    10
5145.0      9
           ..
51983.0     1
14773.0     1
11100.0     1
22046.0     1
22025.0     1
Name: total_likes_on_outstation_checkin_given, Length: 7888, dtype: int64
```

It is likes on the outstation check ins whenever done by every user.

6. yearly_avg_Outstation_checkins

```
['1' '24' '23' '27' '16' '15' '26' '19' '21' '11' '10' '25' '12' '18' '29'
 nan '22' '14' '20' '28' '17' '13' '*' '5' '8' '2' '3' '9' '7' '6' '4']
1     4543
2      844
10     682
9      340
7      336
3      336
8      320
5      261
4      256
16     255
6      236
11     229
24     223
29     215
23     215
18     208
15     206
26     199
20     199
25     198
28     180
19     176
14     167
17     160
12     159
22     152
13     150
21     143
27      96
*        1
Name: yearly_avg_Outstation_checkins, dtype: int64
```

We found that one of the value in column ‘yearly_avg_Outstation_checkins’, is ‘*’. We shall impute it with the mode because the datatype is ‘object’. After the imputation, for further analysis the datatype of variable was changed to ‘float’.

7. member_in_family

```
['2' '1' '4' 'Three' '3' '5' '10']
3        4561
4        3184
2        2256
1        1349
5         384
Three      15
10         11
Name: member_in_family, dtype: int64
```

In the column ‘member_in_family’, one of the data point is ‘Three’ instead of ‘3’. So, ‘Three’ was replaced to ‘3’.

8. Preferred_location_type

```
['Financial' 'Other' 'Medical' nan 'Game' 'Social media' 'Entertainment'
 'Tour and Travel' 'Movie' 'OTT' 'Tour  Travel' 'Beach' 'Historical site'
 'Big Cities' 'Trekking' 'Hill Stations']
Beach              2424
Financial          2409
Historical site    1856
Medical            1845
Other               643
Big Cities          636
Social media        633
Trekking            528
Entertainment       516
Hill Stations       108
Tour  Travel         60
Tour and Travel      47
Game                 12
OTT                   7
Movie                 5
Name: preferred_location_type, dtype: int64
```

In the column ‘preferred_location_type’, the attributes ‘Tour Travel’ and ‘Tour and Travel’ are same. Therefore, we have merged ‘Tour Travel’ into ‘Travel and Tour’.

9. Yearly_avg_comment_on_travel_page

```
[ 94.  61.  92.  56.  40.  79.  81.  67.  44.  84.  49.  31.  93.  50.
  51.  80.  96.  78.  45.  82.  53.  83.  58.  72.  48.  42.  41.  86.
  97.  75.  33.  37.  73.  nan  98.  47.  71.   3.  43.  99.  59.  95.
  57.  76.  87.  66.  55.  32.  52.  70.  62.  64.  63.  60. 100.  46.
  39.  77.  91.  54.  34.  90.  65.  36.  88.  35.  89.  68.  85.  69.
  74.  38. 106. 105. 103. 108. 111. 104. 102. 109. 110. 112. 101. 107.
 615. 114. 113. 215. 815. 685. 118. 117. 115. 116. 121. 122. 120. 124.
 119. 125. 123.]
96.0     192
66.0     191
90.0     190
56.0     188
80.0     184
        ...
124.0      3
685.0      1
815.0      1
215.0      1
615.0      1
Name: Yearly_avg_comment_on_travel_page, Length: 100, dtype: int64
```

It is the count of the comments made by any user on the social media post by the company.

10. total_likes_on_outofstation_checkin_received

```
[ 5993  5130  2090 ... 12093  9983  6203]
2377     12
2380     11
2342     11
2096     10
2610     10
         ..
13678     1
10949     1
4906      1
19439     1
6203      1
Name: total_likes_on_outofstation_checkin_received, Length: 6288, dtype: int64
```

It gives the likes received on the personal profile of the user for any out of station check in.

11. week_since_last_outstation_checkin

```
[ 8  1  6  9  0  4  5  2  7  3 10 11]
1     3070
3     1766
2     1700
4     1118
0     1032
5      728
6      654
7      594
9      472
8      428
10     138
11      60
Name: week since last outstation checkin, dtype: int64
```

It gives the number of weeks since the last outstation check in done by the users.

12. following_company_page

```
['Yes' 'No' nan '1' '0']
No     8355
Yes    3285
1        12
0         5
Name: following_company_page, dtype: int64
```

In the column 'following_company_page', some data points are labelled '1' and '0'. Here we have assumed 'No' as '0' and 'Yes' as '1'. Both the 1s and 0s were transformed into yes and no respectively.

13. montly_avg_comment_on_company_page

```
[ 11  23  15  12  13  20  22  21  17  14  16  18  19  24  25  30  29  28
  27 376 381  26 427 437 499 363 425 439 301 461 322 324 355 338 332 459
 460 453 300 474 368 352 445 310 323 490 371 444 343 417 393 463 350 432
 412 379 336 441 346 317 406 485 400 483 478 438 354 313 497 325 419 388
 398 378 397 349 356 420 347 500 442 435 447 484 330 326 360 403 465 365
 353 429 345 321 491 476 475 487 316 428 472 314 405 473 339 342 455 469
 399 422 370 361 467 458 304 410 383 466 446 302 486 333 418 351 391 468
 454 329 390 384 404 402 424 488 440 312 449 477 380 357 414 337  33  32
  31  34  35  36  37  40  38  41  39  43  42  45  44  47  46  48]
23     673
22     653
25     609
24     605
21     594
      ...
447      1
500      1
347      1
420      1
48       1
Name: montly_avg_comment_on_company_page, Length: 160, dtype: int64
```

This variables gives the average number of comments done on company page on a monthly basis.

14. working_flag

```
['No' 'Yes']
No     9952
Yes    1808
Name: working_flag, dtype: int64
```

The number of users working are 1808 and the non-working users are 9952.

15. travelling_network_rating

```
[0 1 3 2]
0    5048
1    4768
2    1264
3     680
Name: Adult flag, dtype: int64
```

The variable 'travelling_network_rating' is categorical variable but by default it is 'int64'. Therefore the data type of the variable was changed to 'category'.

16. Adult_flag

```
[0 1 3 2]
0    5048
1    4768
2    1264
3     680
Name: Adult flag, dtype: int64
```

In the column 'Adult_Flag', the variable is categorical but by default it is 'int64'. Therefore the data type of the variable was changed to 'object'.

17. Daily_Avg_mins_spend_on_traveling_page

```
34      62
33      60
36      56
35      48
37      46
0       46
40      32
38      30
39      26
41      20
44       8
42       6
43       4
45       4
46       3
135      1
170      1
235      1
270      1
47       1
Name: Daily_Avg_mins_spend_on_traveling_page, dtype: int64
```

This variables tells about the daily average minutes spend by the user on the travelling page.

Understanding the categorical features of data

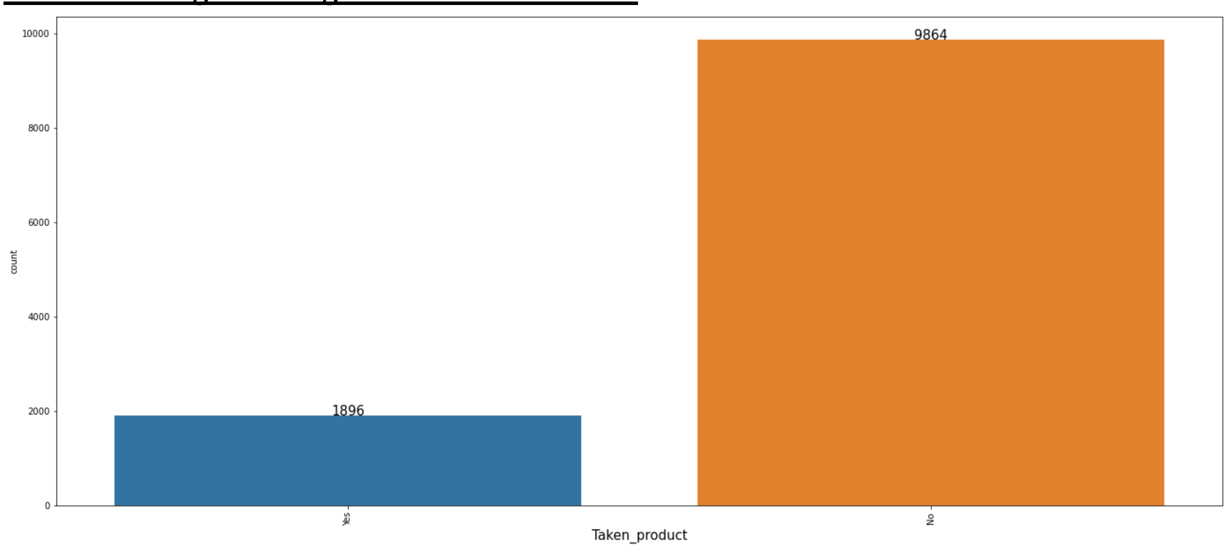


Fig 1

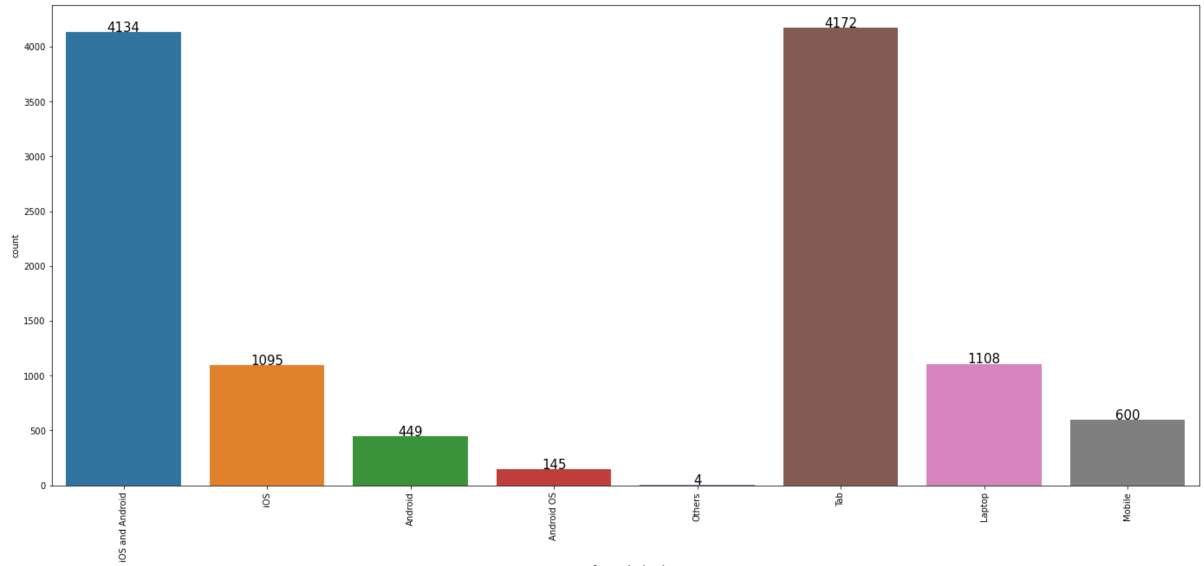


Fig 2

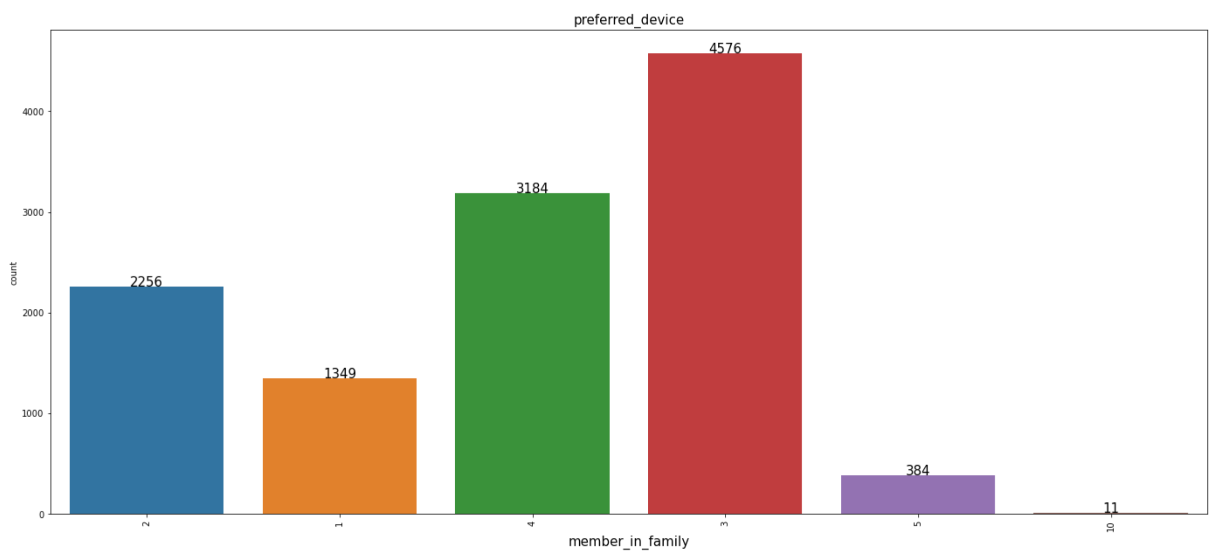
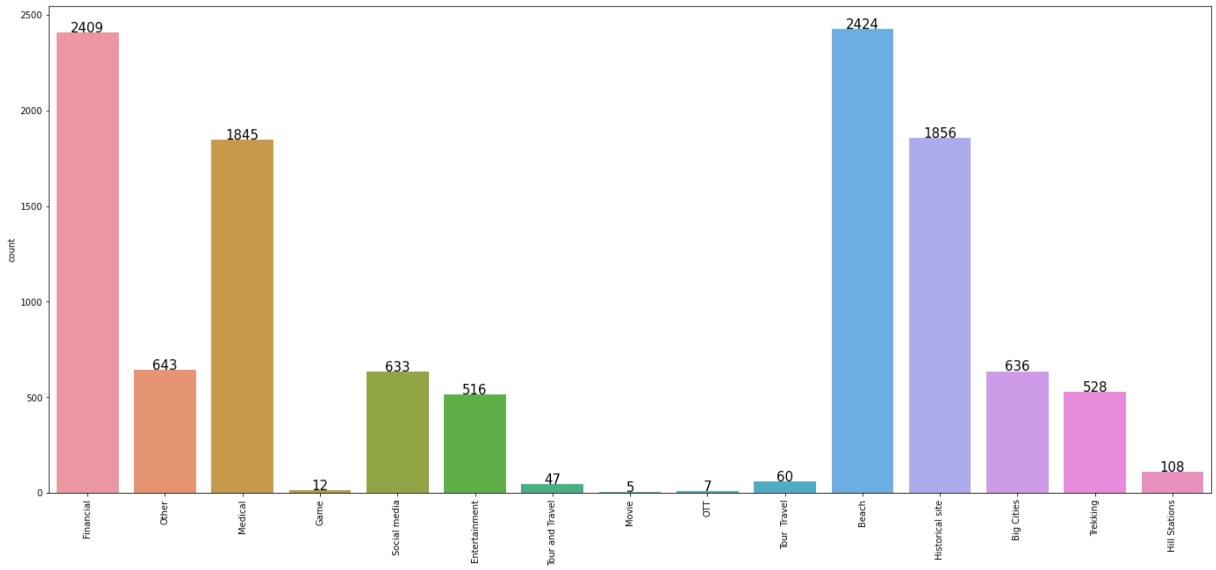
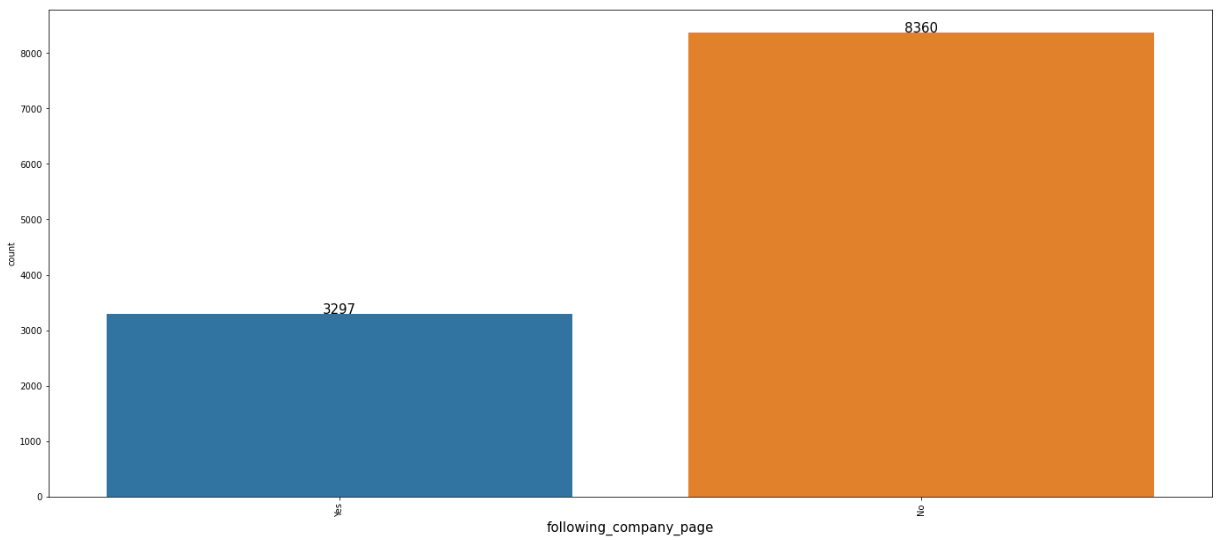


Fig 3



2500
2000
1500
1000
500
0
count
2409
643
1845
12
633
516
47
5
7
60
2424
1856
636
528
108
Financial
Other
Medical
Game
Social media
Entertainment
Tour and Travel
Movie
OTT
Tour Travel
Beach
Historical site
Big Cities
Trekking
Hill Stations

Fig 4



8000
7000
6000
5000
4000
3000
2000
1000
0
count
3297
8360
Yes
No
following_company_page

Fig 5

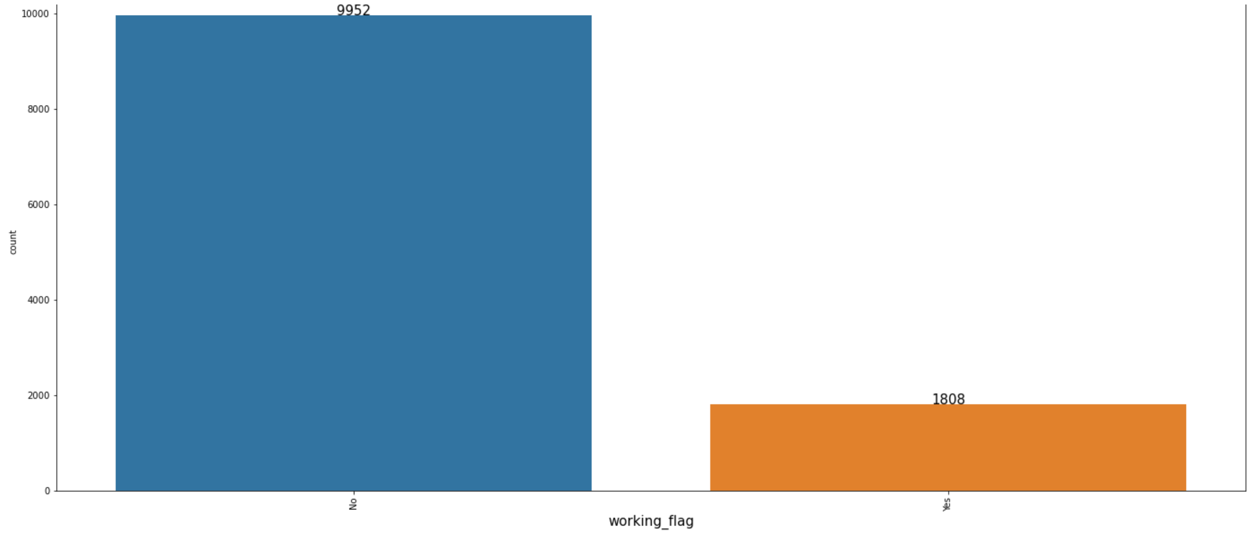

9952
1808
10000
8000
6000
4000
2000
0
count
No
Yes
working_flag

Fig 6

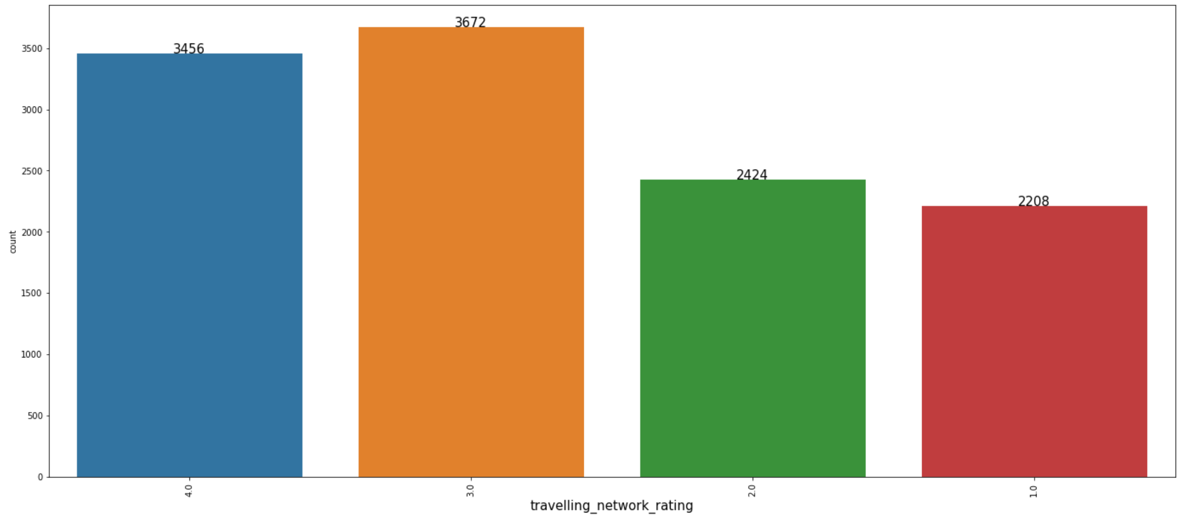


Fig 7

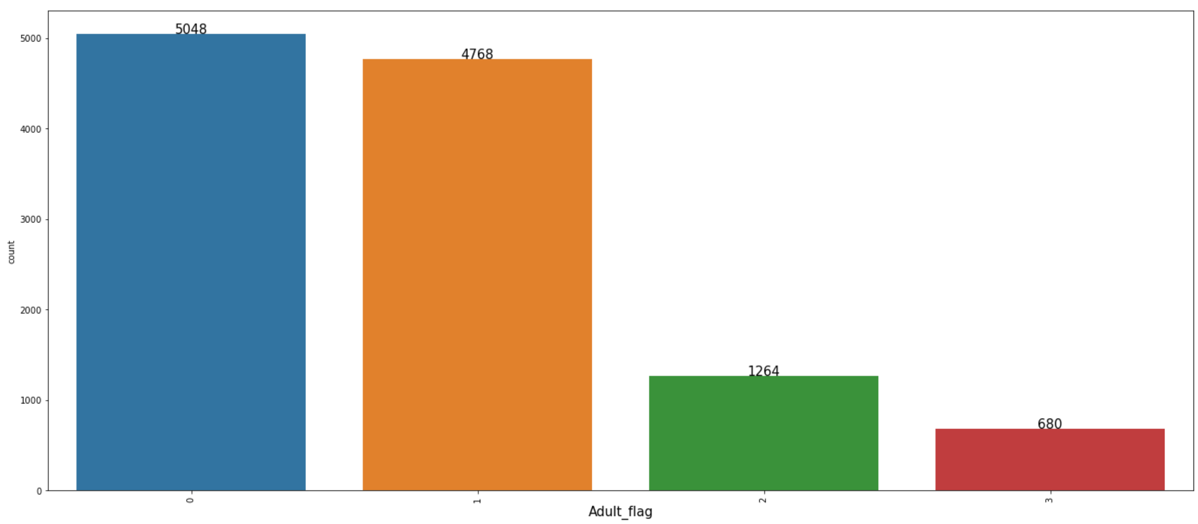


Fig 8

- The above the figures i.e. Fig 1, Fig 2, Fig 3, Fig 4, Fig 5, Fig 6, Fig 7, Fig 8 and Fig 9 belong to the categorical variables.
- In Fig 1, we can see from product taken ‘yes’ that the number of people who bought the product is 9864 and the number of people not going to buy is 1896
- In Fig 2, we understood that the number of prospects is less on Laptop and more on mobiles or tablets. Among non-Laptop devices more number belongs to tab. From operating system (OS), we cannot identify the device because both Android and iOS works well on mobiles as well as tablets.
- From Fig 3, it is visible that most number of families has number of family members as 3. It is followed by 4 members per family.

- From Fig 4, we can understand that the most of the prospects are interested in visiting a beach. It is followed by financial destinations and historical sites respectively. Social media campaign, if aligned with photos related to beach may attract higher traffic.
- From Fig 5, it can be noticed that the number of customers are not following the company page. The number of followers is 3297 where as customers not following are 8390. During, social media campaign videos there should be a reminder given to the customers to follow the page. If they are really interested then they get latest updates, promotions, discounts and other offers launched by the company. This will definitely increase the sale in the travel ticket.
- In Fig 6, we get the number of working customers. We can see that the working people are 9952 and non- working are 1808.
- From Fig 7, the ratings can be understood. The customers have rated 3 stars out 4 in most number of cases. The total of 3 & 4 ratings is 7128. However, the number of customers moderately liking or not giving good rating is also significant.
- Fig 8 belongs to the Adult_flag, the data has some anomalies because of which we can see 4 categories. Actually, categories should be two only i.e. Adult or Not Adult.

<u>Understanding the numeric features of dataset</u>

For understanding the numeric variables, we have plotted the distribution and box plot.

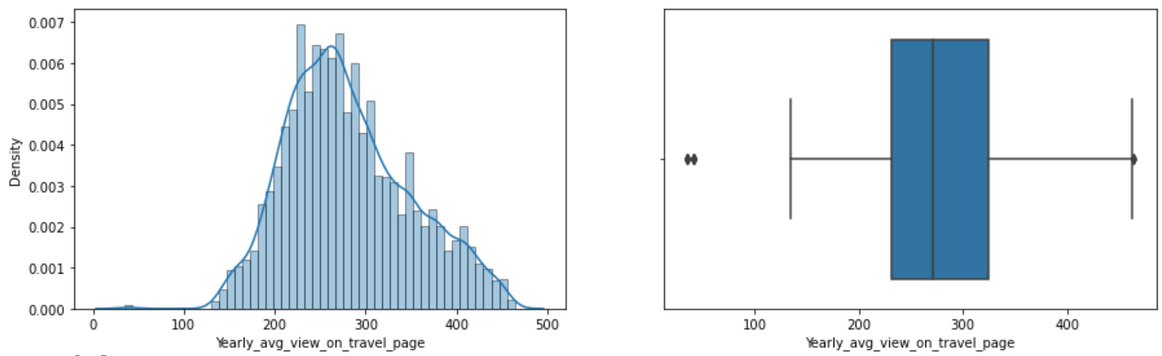


Fig 9

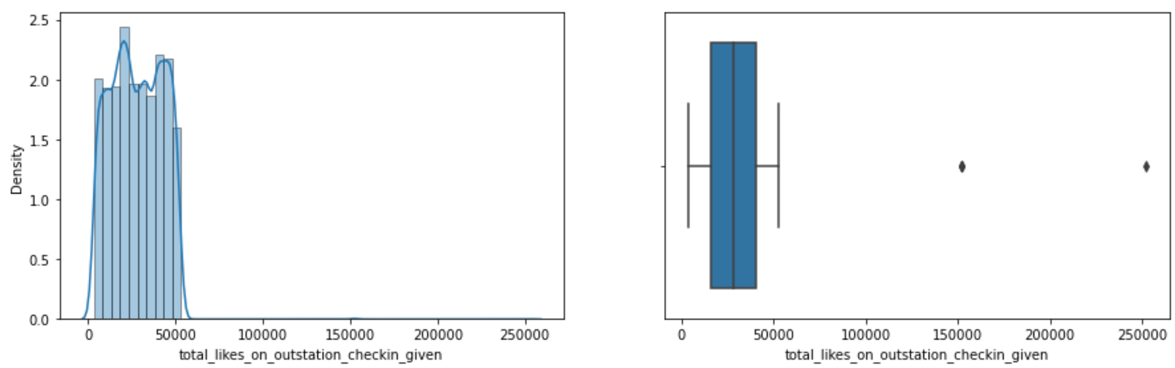


Fig 10

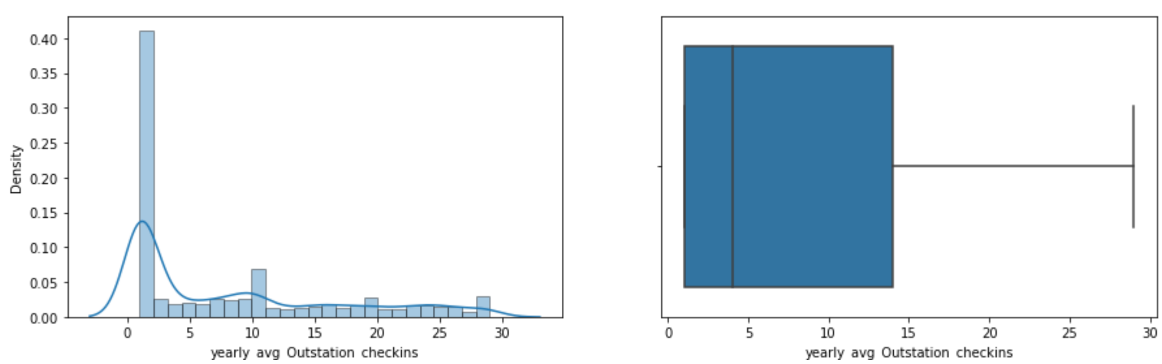


Fig 11

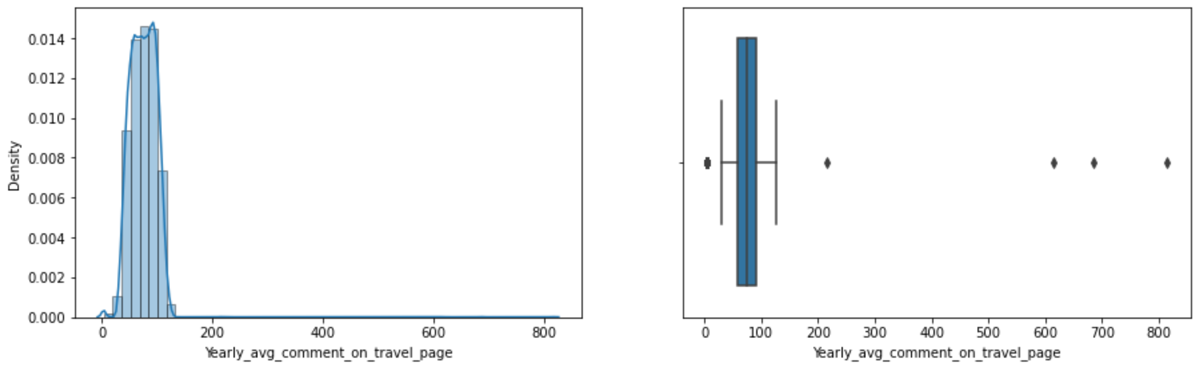


Fig 12

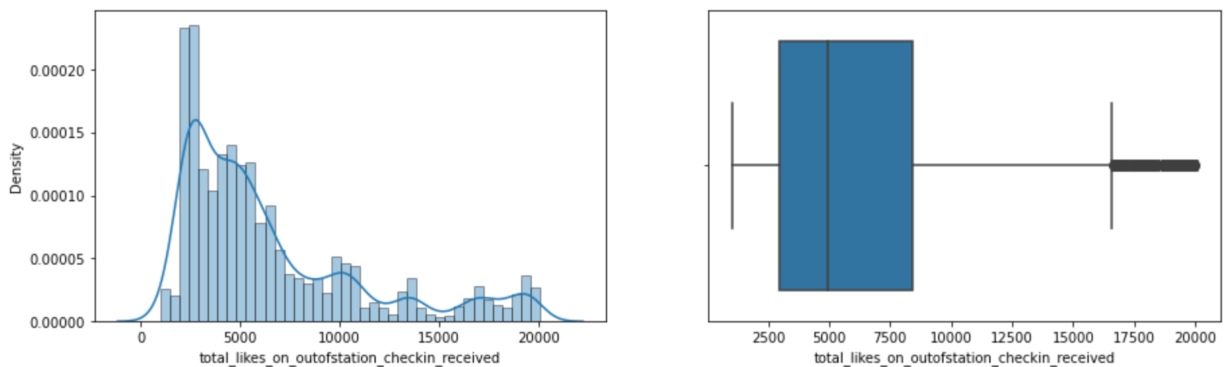


Fig 13

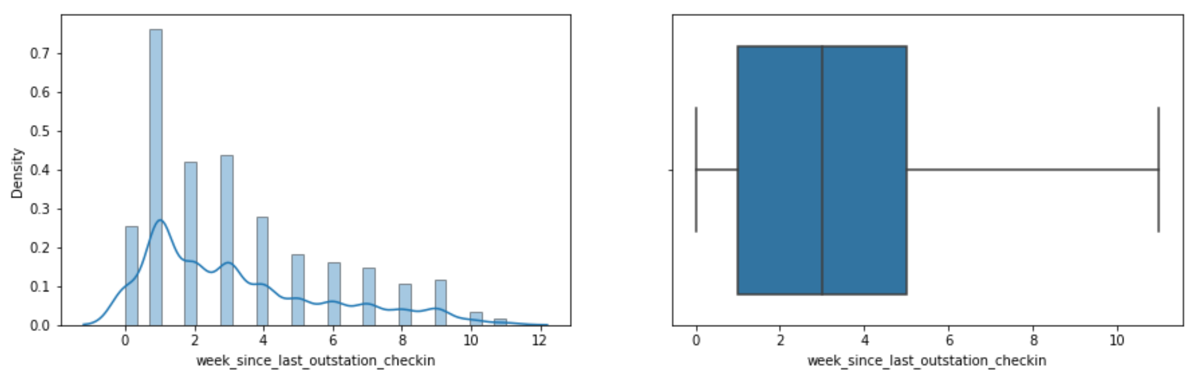


Fig 14

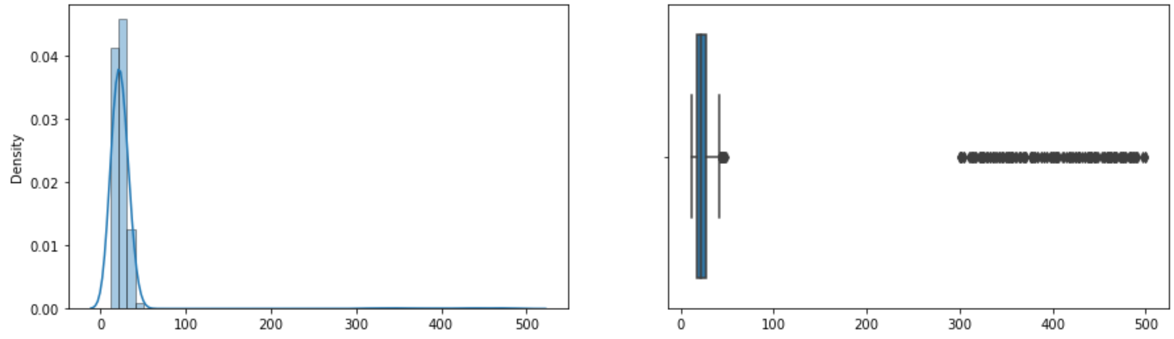


Fig 15

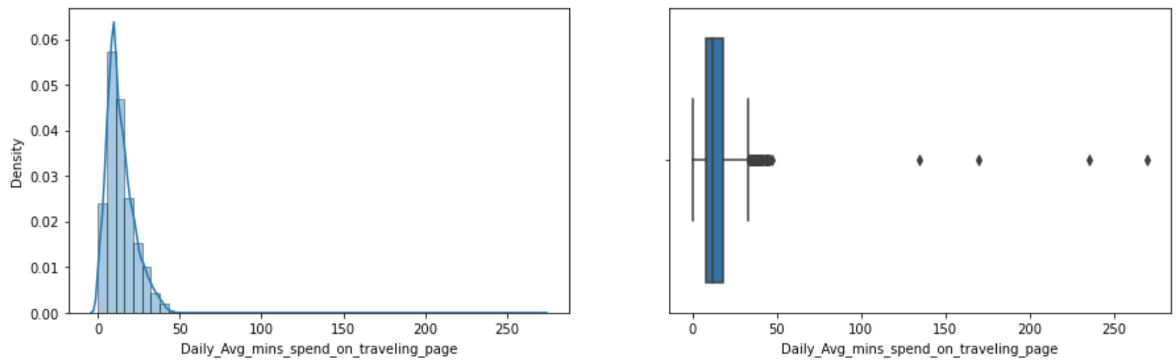


Fig 16

- In Fig 9, we can see that the variable is near to the normal distribution but it has presence of outliers in it.
- In Fig 10, we can see that the data is not normally distributed and it has outliers
- In Fig 11, we can see that the data is right skewed and it does not have outliers
- Fig 12 has the data that is not normally distributed and it has outliers
- In Fig 13, we can see that the data is right skewed and it has too many outliers
- In Fig 14, we can see that the data is right skewed and it does not have outliers
- In Fig 15, we can see that the data is right skewed and it has too many outliers
- In Fig 16, we can see that the variable is near to the normal distribution but it has presence of outliers in it.

b) Bivariate Analysis

We shall understand the bivariate analysis of categorical variables through count plots.

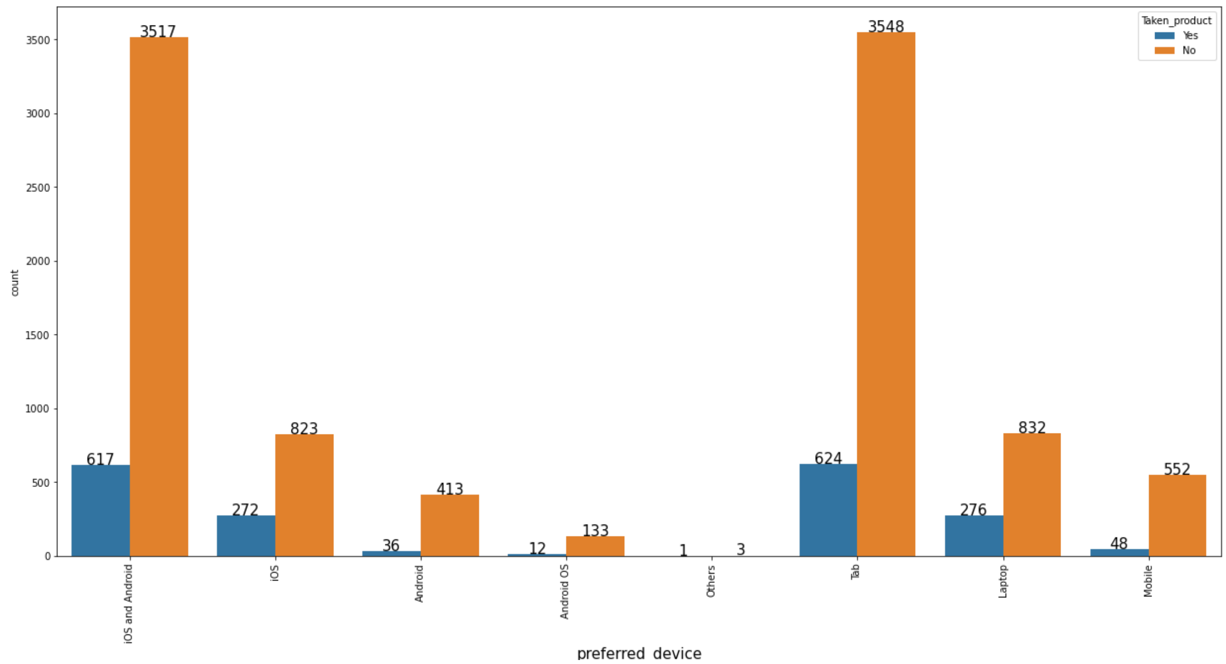


Fig 17

In Fig 17, we can see that most number of customers buying the tickets belongs to 'Tab' and 'iOS and Android'. This means that most of the people buying the ticket are using less of laptop to access the social media campaign. This gives us the understanding that more campaigns should be done on mobile devices compared to laptops.

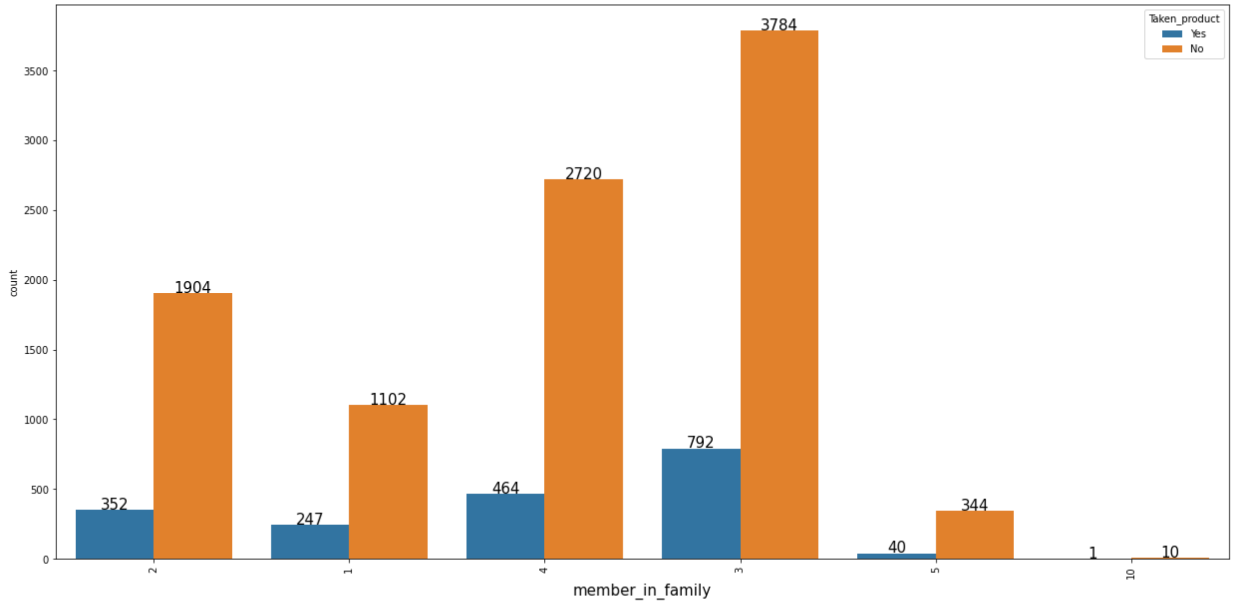


Fig 18

From Fig 18 we can understand that families where number of members are 3 are more likely to buy the ticket. It is followed by number of family member 4 and then 2. We can also understand that where only a member is there has less occurrence of buying. Also, where number of members is large has less occurrence of buying ticket.

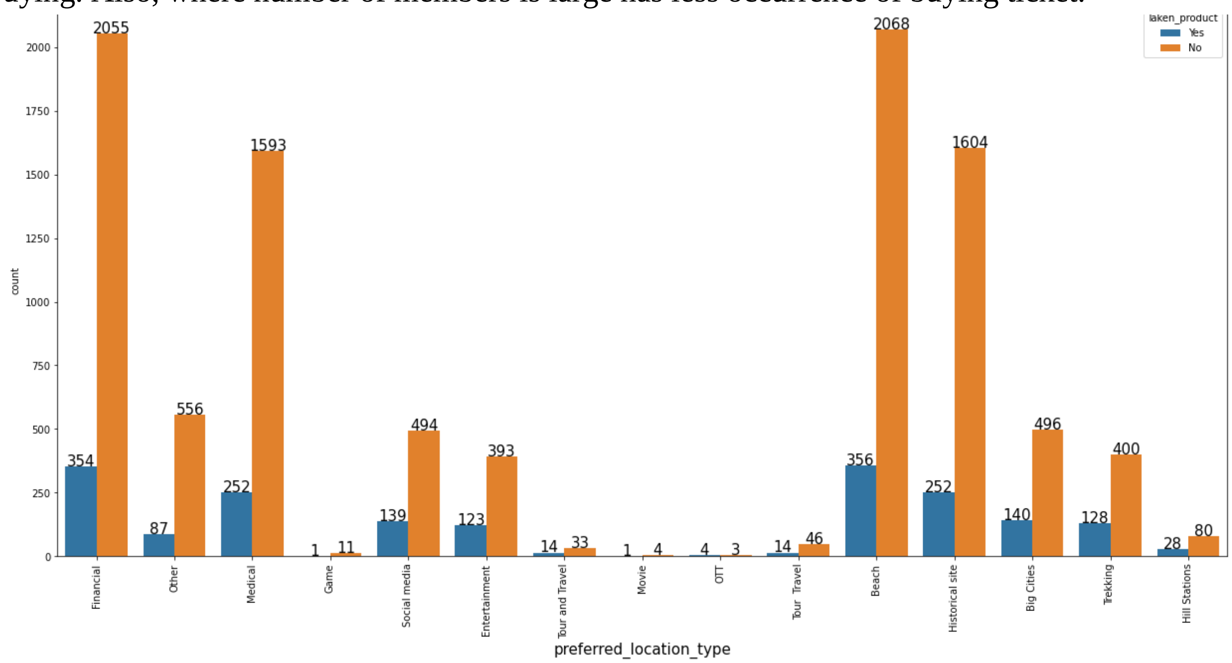


Fig 19

From Fig 19, we can understand that the most favorite destination for people buying the ticket is beach and financial places. The number of customers opting in both the places is almost equal. It is followed by 'Medical' and 'Historical' places.

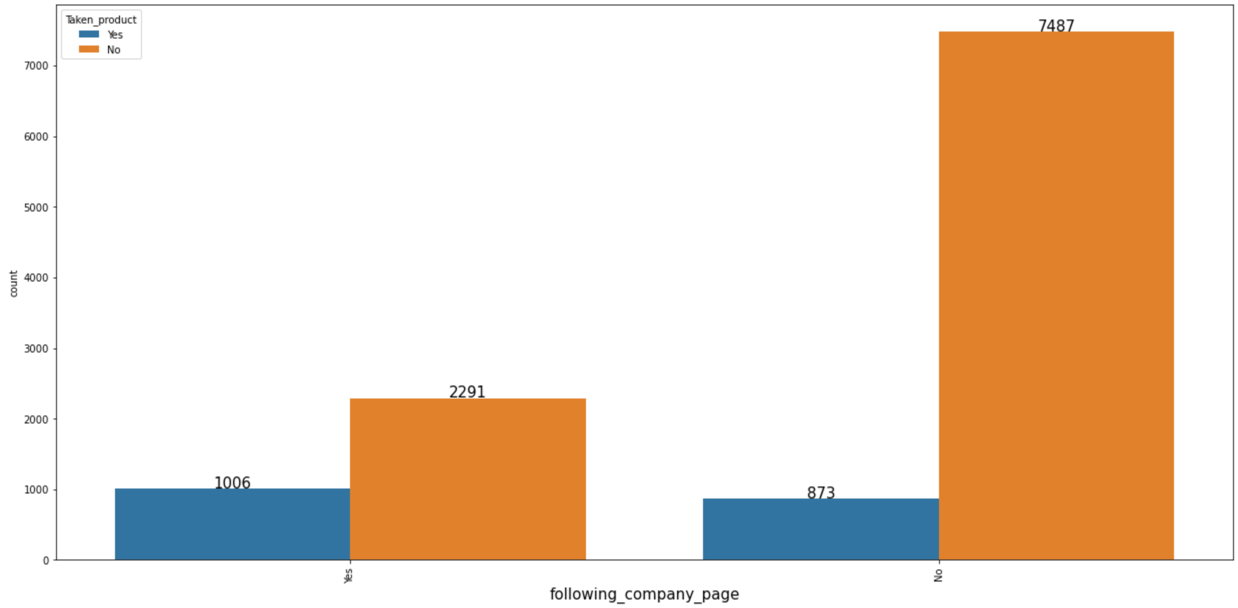


Fig 20

From Fig 20, we can understand that the audience who follow the social media page has more taken the product more than those who do not follow the page.

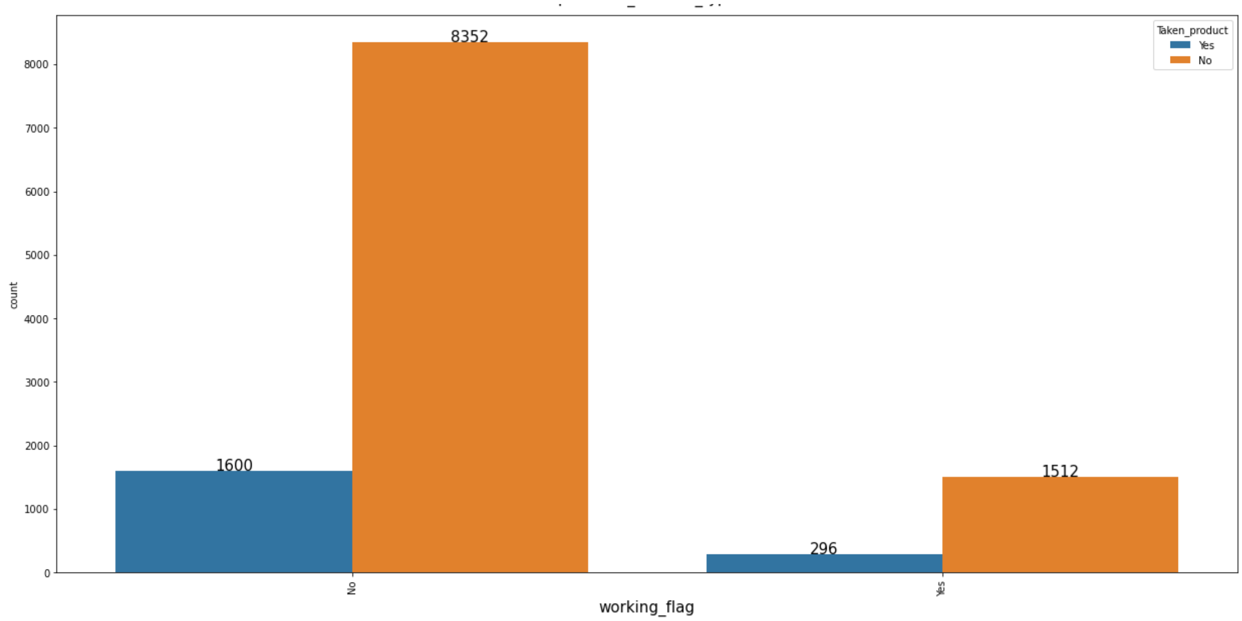


Fig 21

Here from Fig 21, we can understand that working people has very high chances of going to buy the ticket as compared to the non-working audience.

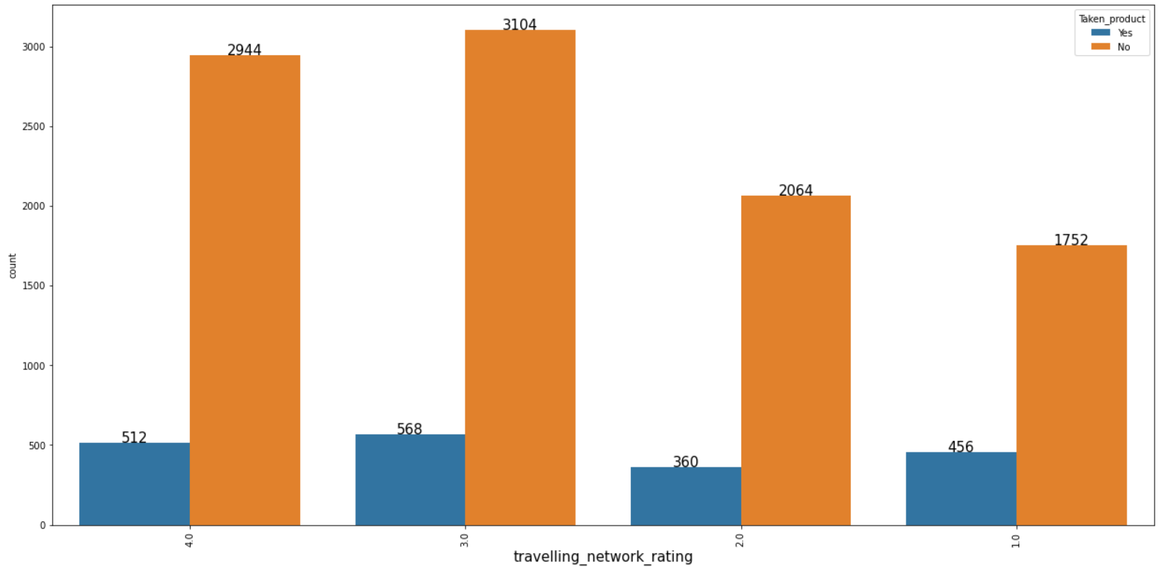


Fig 22

From Fig 22, we can understand that the rating has influenced the buying of ticket. The people who have rated 3 and 4 stars have taken product more as compared to the people giving 1 and 2 rating.

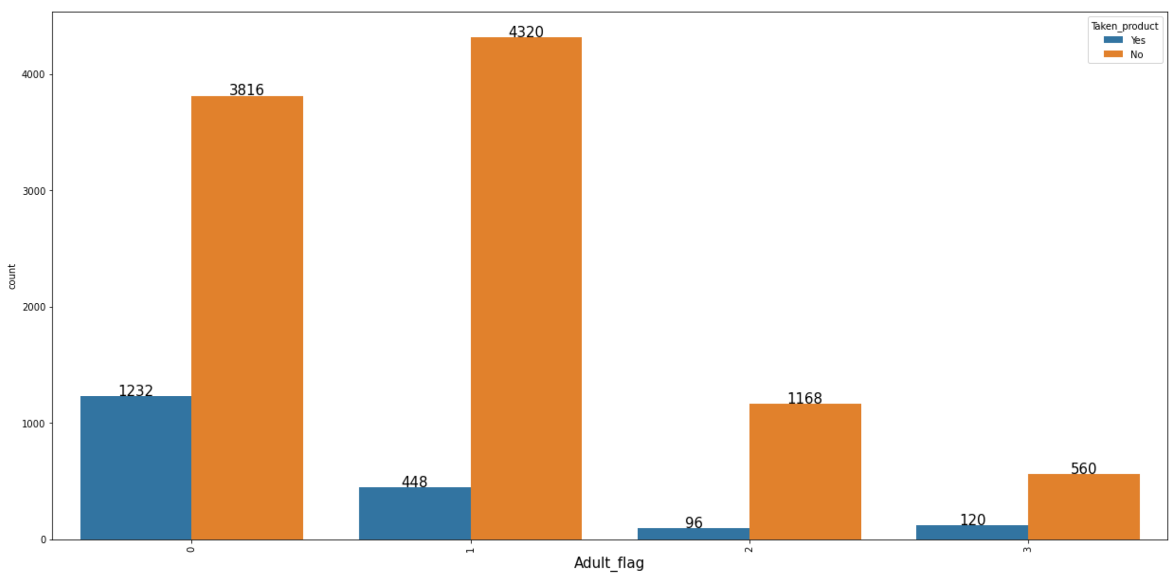


Fig 23

From Fig 23, we can understand that the people who are not adults have opted product more than the people who are adults.

Now, we shall understand the bivariate analysis of numerical variables through the boxplots.

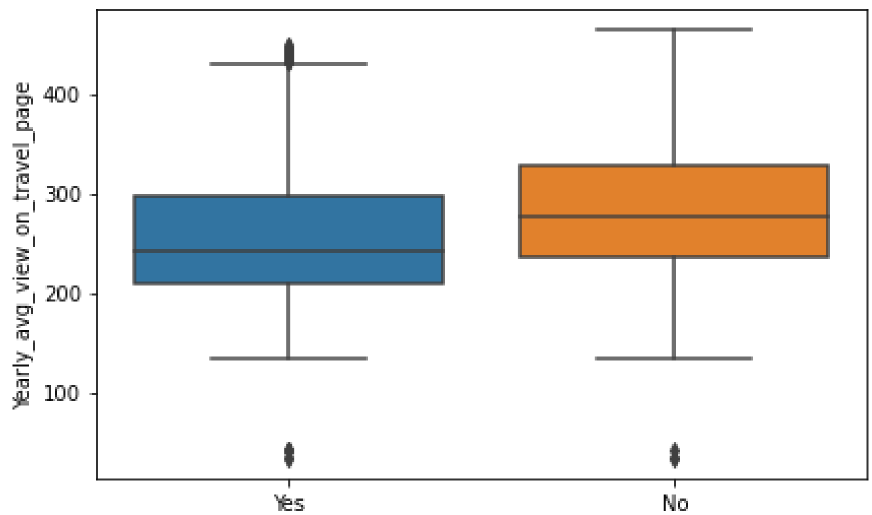


Fig 24

From Fig 24 we can understand the people who have spent significant time on the social media page haven't bought the ticket. The people who have taken the product has less view time average on social media page.

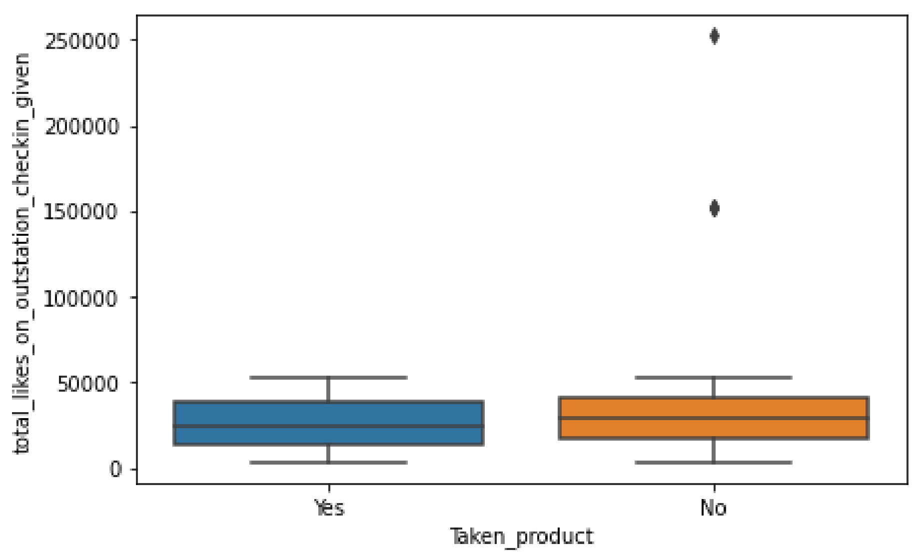


Fig 25

From the Fig 25 we can understand that the people liking the social media has more chances of buying the product.

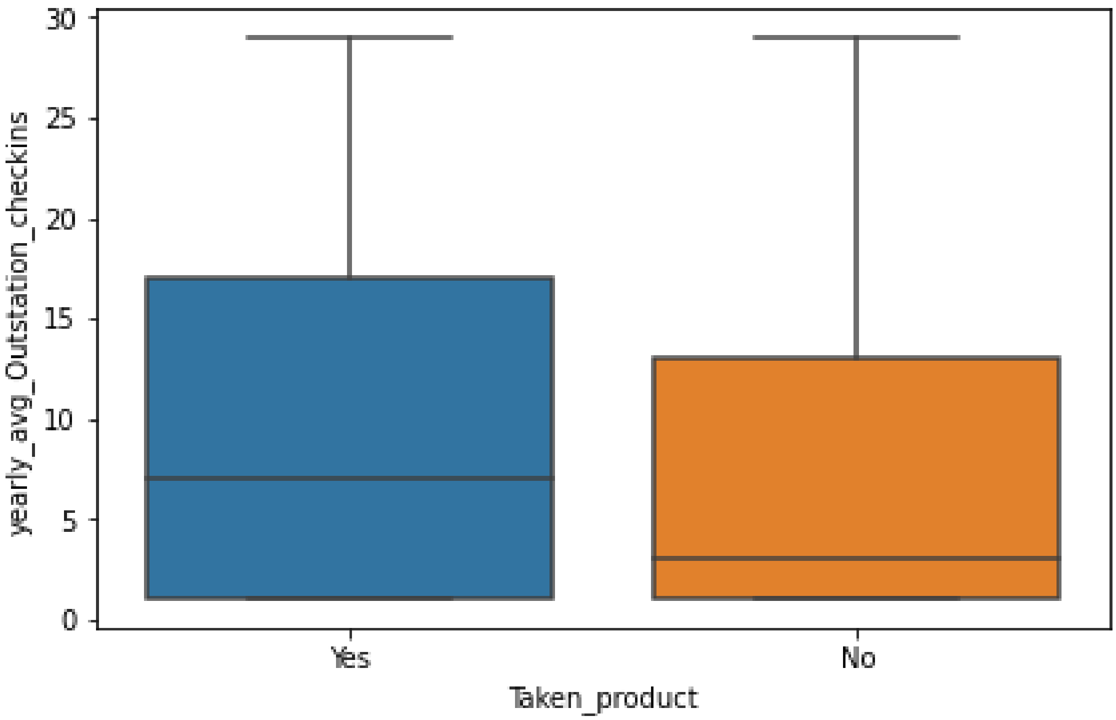


Fig 26

From Fig 26 we can understand that the people often going to outstation trips have more opted to take the product as compared to those who go out very less.

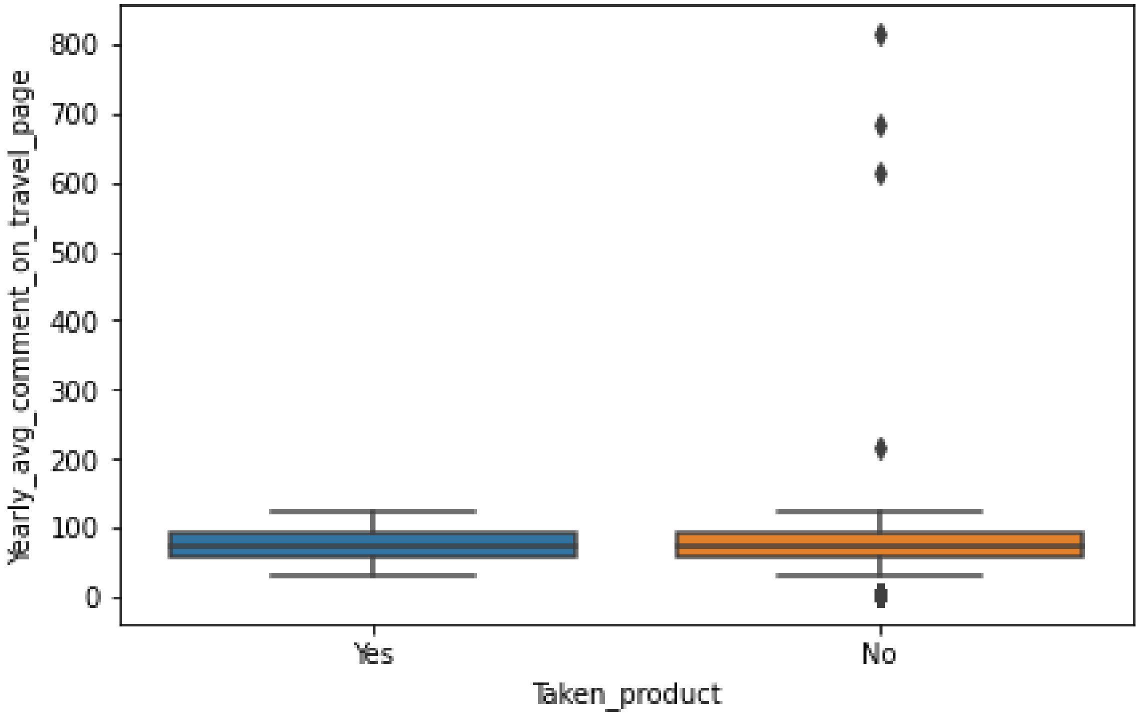


Fig 27

From Fig 27 we can understand that the people commenting on the social media page does not take significant effect on buying the ticket.

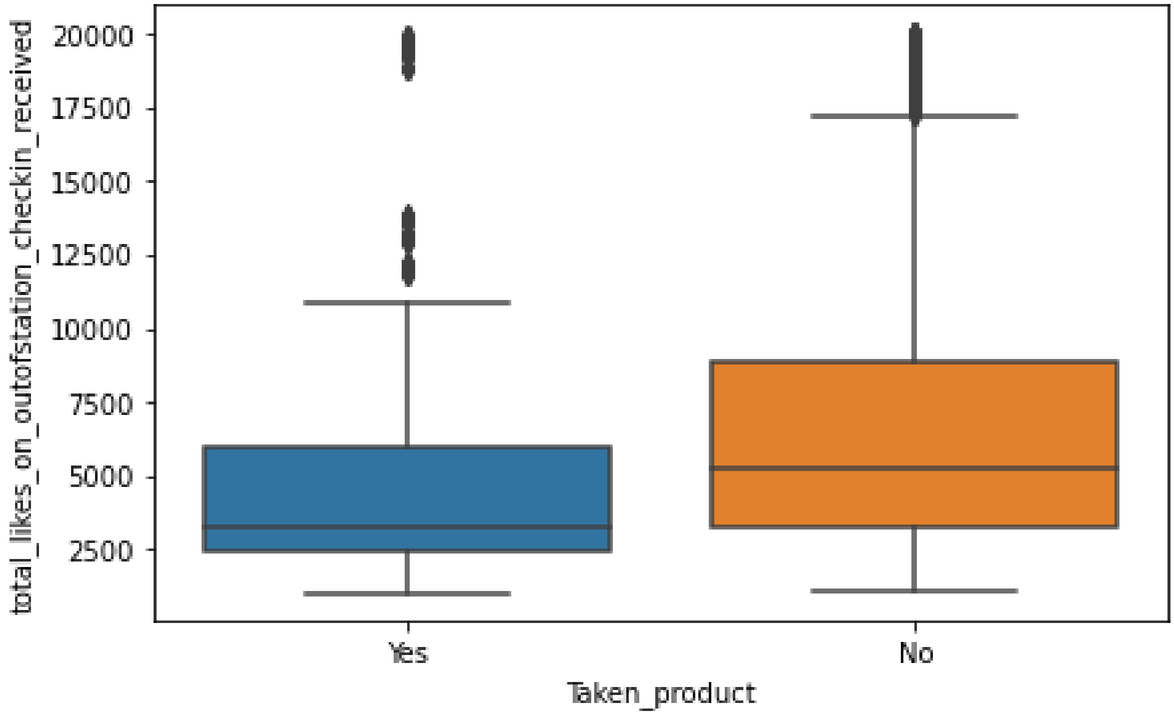


Fig 28

From Fig 28, we can understand that the likes on outstation check-ins does not have significant effect on buying pattern of a customer.

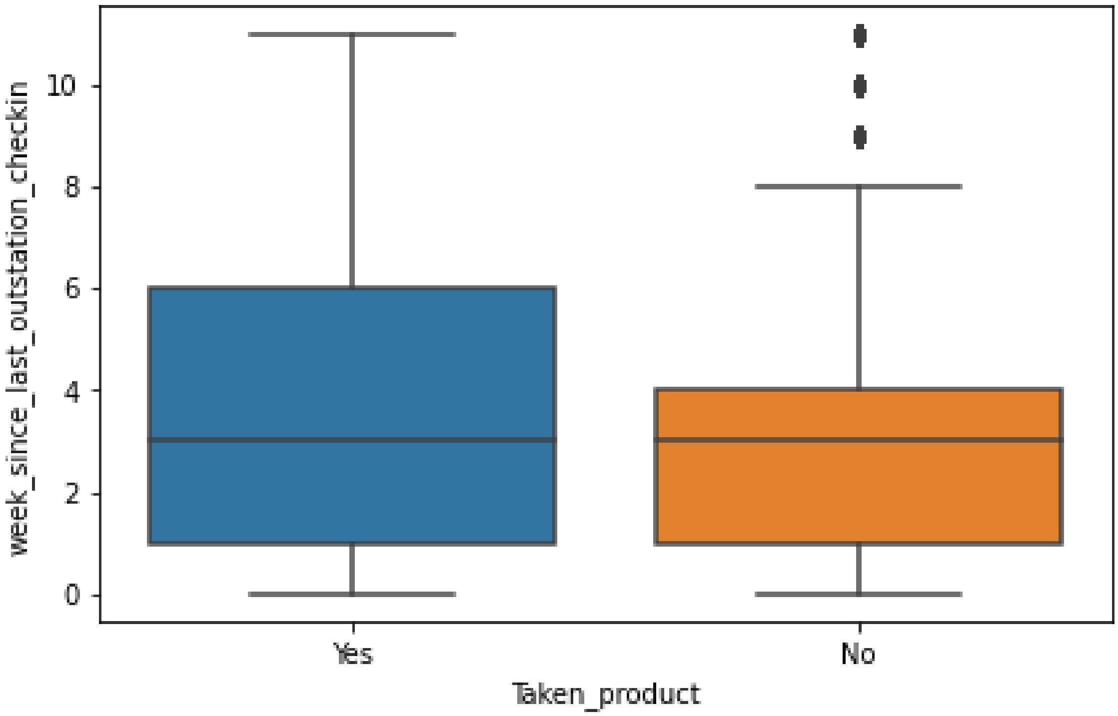


Fig 29

From Fig 29, we can understand that the more weeks since last outstation checking has more opted for going to buy the ticket.

Correlation Matrix

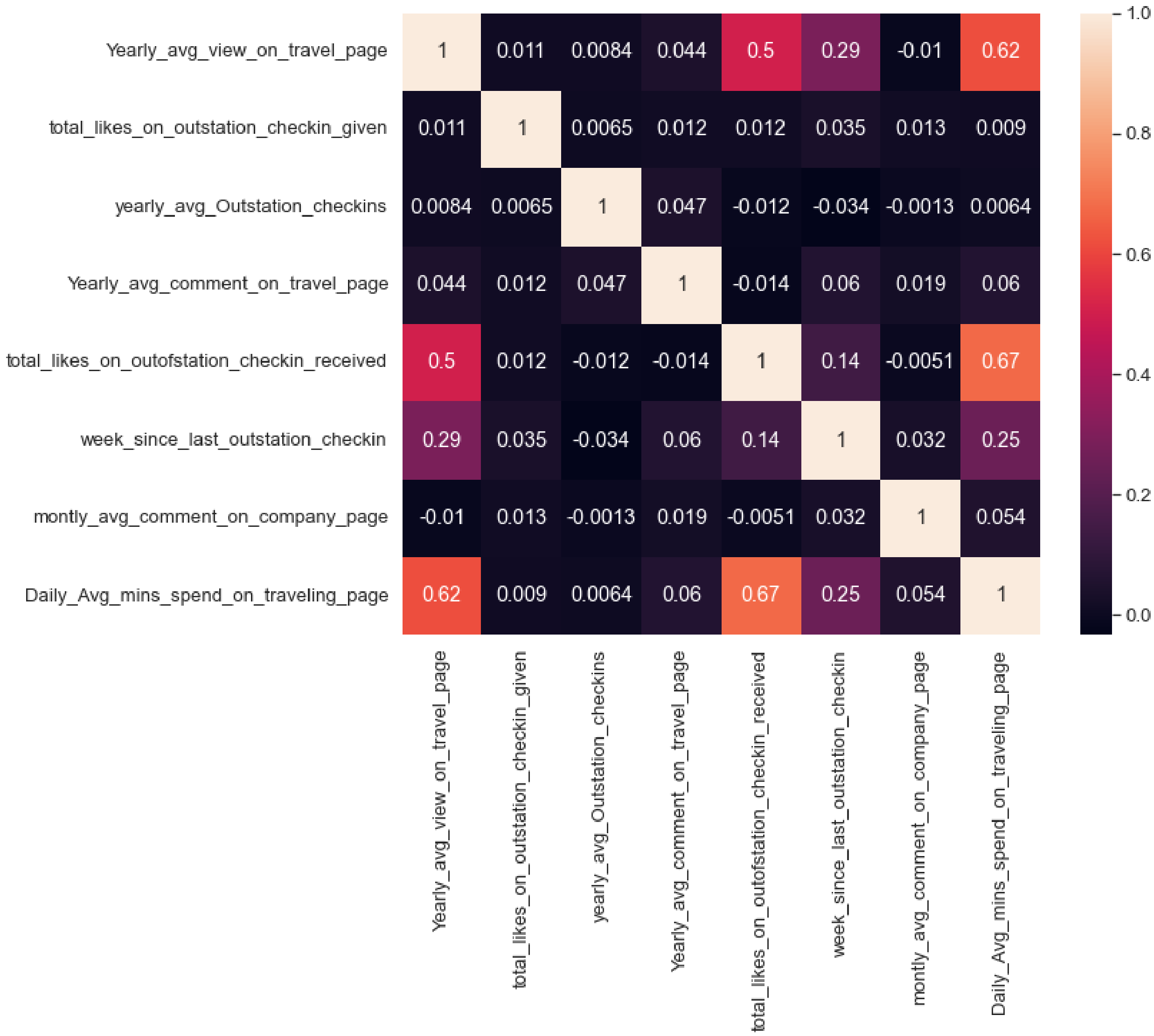


Fig 30

- From Fig 30 we can understand that there is high correlation of 0.67 between “Daily average minutes spend on travelling page” and “total likes on outstation checkin received”
- There is moderate correlation of 0.62 between “Daily average minutes spend on travelling page” and “yearly average view on travel page”

- There is low correlation of 0.5 between "yearly average view on travel page" and "total likes on outstation checkin received"

c) <u>Missing Value Treatment</u>

During the univariate analysis and the bivariate analysis, we had divided the dataset into two parts. One part composed of 'categorical' & 'object' features. Whereas the other part composed of integer as well as float data types.
In the categorical variables we have used mode for the missing value treatment.
In case of numerical variables, we have used median imputation method for the missing value treatment. Median is the best measure of central tendency to fill in missing values.
Below are the categorical variables after NULL value treatment.

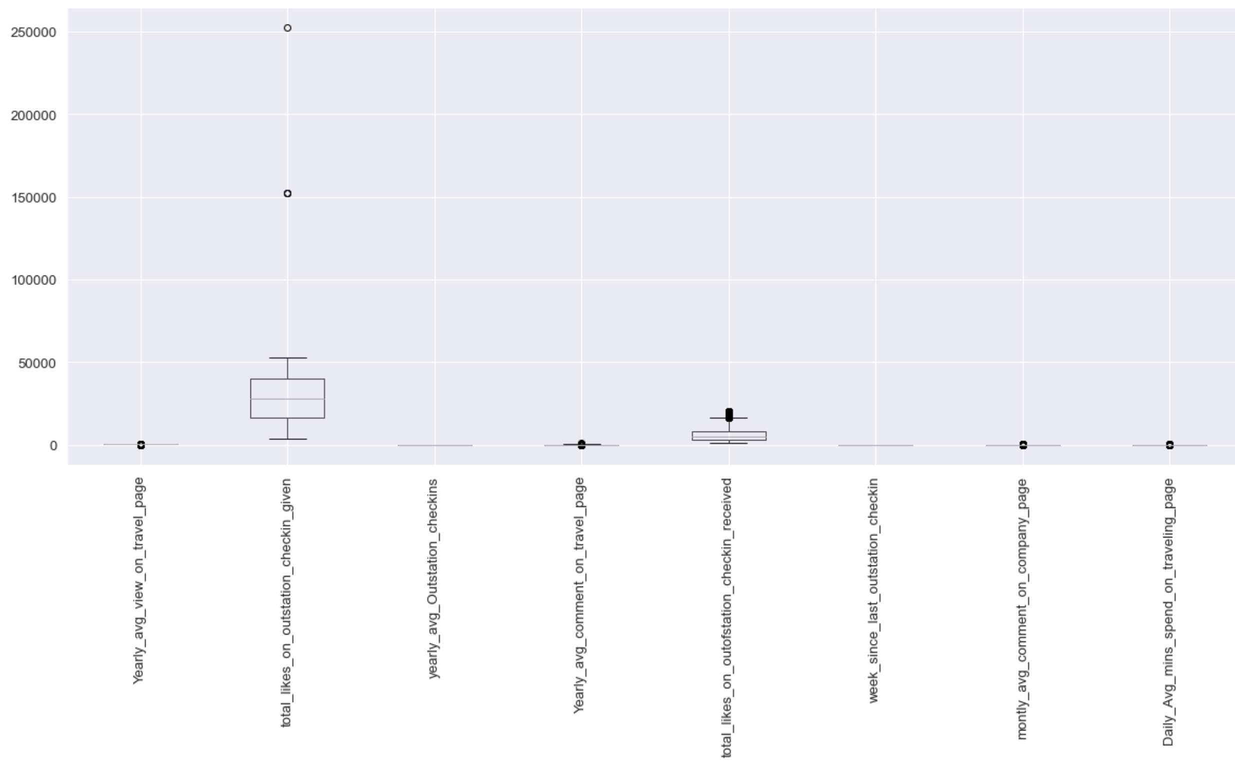
```
Taken_product                0
preferred_device             0
member_in_family             0
preferred_location_type      0
following_company_page       0
working_flag                 0
travelling_network_rating    0
Adult_flag                   0
dtype: int64
```

Below are the numerical variables after NULL value treatment.

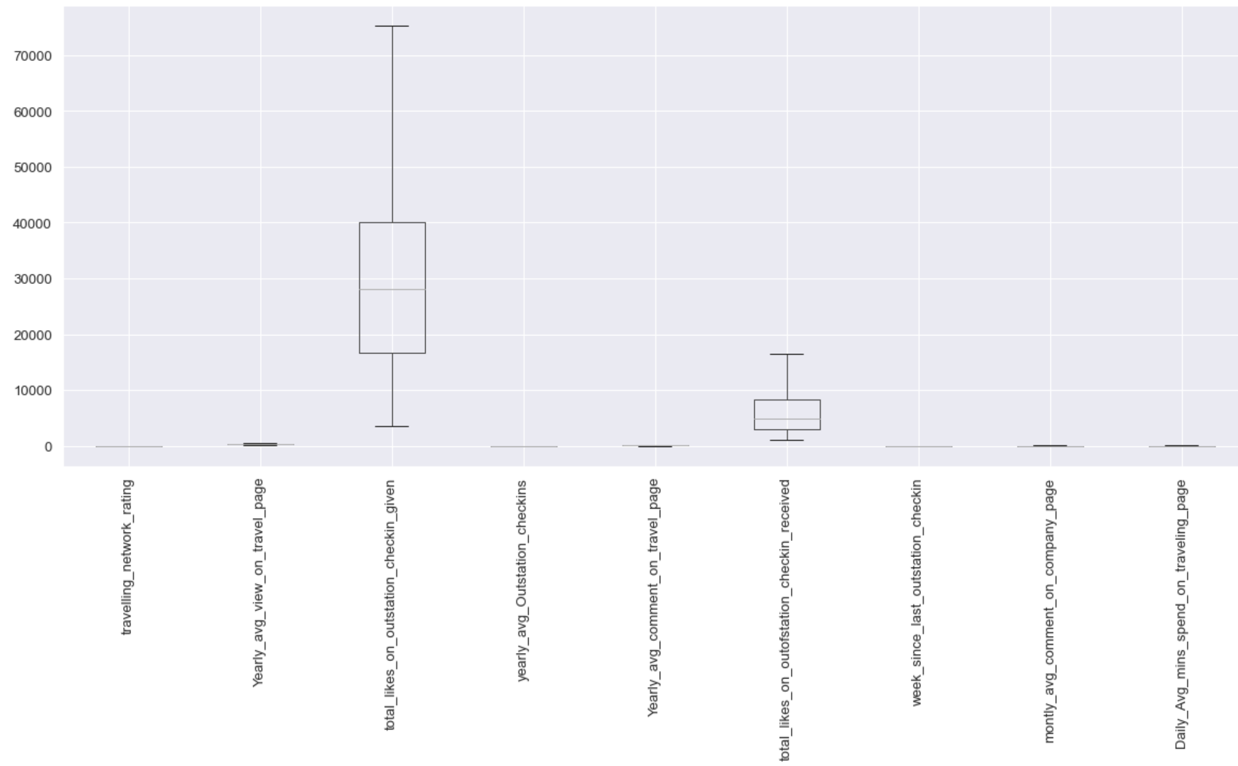
```
Yearly_avg_view_on_travel_page                 0
total_likes_on_outstation_checkin_given        0
yearly_avg_Outstation_checkins                 0
Yearly_avg_comment_on_travel_page              0
total_likes_on_outofstation_checkin_received   0
week_since_last_outstation_checkin             0
montly_avg_comment_on_company_page             0
Daily_Avg_mins_spend_on_traveling_page         0
dtype: int64
```

d) Outlier Treatment

Below is the data before the outlier treatment.



In the above graph we can see that all the variables have outliers except "week since last outstation check-in". We shall be treating the outliers by imputing them with the standard technique of imputing with upper quantile and lower quantile limits. The upper value is calculated by Q3+(1.5 * IQR) & lower value is calculated by Q1-(1.5 * IQR). After imputation the data looks like the following image.



e) <u>Variable Transformation & Addition of new variable</u>

1. In the beginning of the project only we understood the fact that the social media page of the company is viewed by majorly two types of devices. These devices are Laptop and Mobile. The categories like tablet, Android, iOS, Mobile and Others shall fall under category “Mobile”. Remaining data points shall come under category “Laptop”.
   Therefore, we have to we have done variable transformation of all the variables which are not Laptop into “Mobile”. A new variable was created labelled “Mobile_Or_Laptop”. Subsequently a new variable was created called “Labelled_Mobile_Or_Laptop” where “Laptop” is labelled 0 and “Mobile” was labelled as 1.
2. In case of working_flag, the data points with ‘Yes’ are labelled as 1 and ‘No’ are labelled as 0. These changes are incorporated in a new variable called “Labelled_working_flag”.
3. In case of Taken_product, the data points with ‘Yes’ are labelled as 1 and ‘No’ are labelled as 0. These changes are incorporated in a new variable called “Labelled_ Taken_product”.

4. In case of following_company_page, the data points with ‘Yes’ are labelled as 1 and ‘No’ are labelled as 0. These changes are incorporated in a new variable called “Labelled_ following_company_page”.
5. In case of preferred_location_type, the data points were labelled from 14 to 1. 14 is the most preferred location, whereas 1 is the least preferred location. These inferences were drawn from the frequency of occurrence of each destination which is mentioned below for reference. These changes are incorporated in a new variable called “Labelled_ preferred_location_type”.

Beach	2424
Financial	2409
Historical site	1856
Medical	1845
Other	643
Big Cities	636
Social media	633
Trekking	528
Entertainment	516
Hill Stations	108
Tour Travel	60
Tour and Travel	47
Game	12
OTT	7
Movie	5

6. The variables ‘member_in_family’, ‘yearly_avg_Outstation_checkins’ and ‘Adult_flag’ were converted from categorical variables to float for further analysis.

f) <u>Removal of unwanted variables</u>

1. The following variables were removed-
- 'preferred_device'- Because it was converted into ‘Mobile_Or_Laptop’
- 'preferred_location_type'- It was labelled 1 to 14 and new variable ’Labelled_preferred_location_type’ was created
- 'following_company_page'- Converted to 1 & 0 in new labelled column
- 'working_flag'- Converted to 1 & 0 in new labelled column
- 'Mobile_Or_Laptop'- Converted to 1 & 0 in new labelled column
- 'Taken_product'- Converted to 1 & 0 in new labelled column

4. BUSINESS INSIGHTS from EDA

a) Is the data unbalanced? If so, what can be done? Please explain in the context of the business

Yes the data is unbalanced. The social media campaign was targeted on 11760 social media users. Out of which only 1896 customers ended up buying the ticket from the company which is roughly 16.12%. On the other hand, the audience not taking the product is very high i.e. 9864 which constitutes 83.88% of the total users.

Therefore, the campaign should be targeted on the audience who has high probability of buying the ticket. This should be done based on understanding the social and digital behavior of the existing customers.

For the business of GO-GO Air, this is an alarming situation. The management should start thinking on ways to improve the campaigns and targeting it on right people. Essentially, they need to realize that the campaign performance is very poor.

b) The statsmodel technique has been applied to the variables to eliminate the variables which are not contributing. Here after removing the highest p-value in repeated models, the below final variables were obtained. The p-value considered here has to be less than 0.05. Therefore, features were tried and tested manually using backward elimination approach.

Logit Regression Results

Dep. Variable:	Labelled_Taken_product	**No. Observations:**	7879
Model:	Logit	**Df Residuals:**	7867
Method:	MLE	**Df Model:**	11
Date:	Sun, 07 Nov 2021	**Pseudo R-squ.:**	0.1937
Time:	21:53:50	**Log-Likelihood:**	-2805.7
converged:	True	**LL-Null:**	-3479.6
Covariance Type:	nonrobust	**LLR p-value:**	2.164e-282

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	2.1715	0.254	8.540	0.000	1.673	2.670
travelling_network_rating	-0.2125	0.032	-6.714	0.000	-0.275	-0.150
Adult_flag	-0.6138	0.047	-13.175	0.000	-0.705	-0.522
Yearly_avg_view_on_travel_page	-0.0038	0.001	-5.810	0.000	-0.005	-0.003
total_likes_on_outstation_checkin_given	-1.182e-05	2.45e-06	-4.816	0.000	-1.66e-05	-7.01e-06
yearly_avg_Outstation_checkins	0.0356	0.004	9.216	0.000	0.028	0.043
total_likes_on_outofstation_checkin_received	-9.317e-05	1.37e-05	-6.796	0.000	-0.000	-6.63e-05
week_since_last_outstation_checkin	0.1537	0.013	11.420	0.000	0.127	0.180
Daily_Avg_mins_spend_on_traveling_page	-0.0433	0.007	-5.938	0.000	-0.058	-0.029
Labelled_Mobile_Or_Laptop	-0.7637	0.103	-7.413	0.000	-0.966	-0.562
Labelled_following_company_page	1.5742	0.070	22.357	0.000	1.436	1.712
Labelled_preferred_location_type	-0.1054	0.013	-8.117	0.000	-0.131	-0.080

The variables eliminated in the process were ‘Yearly_avg_comment_on_travel_page’, ‘member_in_family’, ‘Labelled_working_flag’, and ‘montly_avg_comment_on_company_page’.

c) Business Insights

- Customers on Mobile are more likely to take the product compared to the customers who access the social media page through Laptop
- In families where number of members are 3 or 4 have high chances of buying the ticket
- Beach, Financial places and Historical sites are most favored destinations, therefore social media campaigns should be based on these topics. This will attract high traffic on social media page
- It was observed that the significant numbers of buyers are not following the social media page. Therefore, they should asked to follow in the videos, posts etc. By doing this, they will updated with promotions, discounts and latest offers launched by the company. This will definitely increase the sale in the travel ticket.
- Working people have high probability of buying the product
- It was observed that the young population who are not even adults are buying more tickets, while creating campaigns this should be taken care