

# Starbucks\_Capstone\_notebook

May 23, 2020

## 1 Starbucks Capstone Challenge

### 1.0.1 Introduction

This data set contains simulated data that mimics customer behavior on the Starbucks rewards mobile app. Once every few days, Starbucks sends out an offer to users of the mobile app. An offer can be merely an advertisement for a drink or an actual offer such as a discount or BOGO (buy one get one free). Some users might not receive any offer during certain weeks.

Not all users receive the same offer, and that is the challenge to solve with this data set.

Every offer has a validity period before the offer expires. As an example, a BOGO offer might be valid for only 5 days. For example, if an informational offer has 7 days of validity, you can assume the customer is feeling the influence of the offer for 7 days after receiving the advertisement.

We are given transactional data showing user purchases made on the app including the timestamp of purchase and the amount of money spent on a purchase. This transactional data also has a record for each offer that a user receives as well as a record for when a user actually views the offer. There are also records for when a user completes an offer.

Someone using the app might make a purchase through the app without having received an offer or seen an offer.

### 1.0.2 Example

To give an example, a user could receive a discount offer buy 10 dollars get 2 off on Monday. The offer is valid for 10 days from receipt. If the customer accumulates at least 10 dollars in purchases during the validity period, the customer completes the offer.

However, there are a few things to watch out for in this data set. Customers do not opt into the offers that they receive; in other words, a user can receive an offer, never actually view the offer, and still complete the offer. For example, a user might receive the "buy 10 dollars get 2 dollars off offer", but the user never opens the offer during the 10 day validity period. The customer spends 15 dollars during those ten days. There will be an offer completion record in the data set; however, the customer was not influenced by the offer because the customer never viewed the offer.

### 1.0.3 Project Overview

In this project, an attempt has been made to analyse how Starbucks customers use the app. The promotion for Starbucks using various offers and are these offers actually helpful. The data sets used in this project contains simulated data that mimics customer behavior on the Starbucks rewards mobile app. The customer's behaviour has been attempted to analyse based on the dataset.

### 1.0.4 Cleaning

Cleaning data is especially important and tricky. From a business perspective, if a customer is going to make a 10 dollar purchase without an offer anyway, you wouldn't want to send a buy 10 dollars get 2 dollars off offer. It is important to assess what a certain demographic group will buy when not receiving any offers.

### 1.0.5 Analysis

**Business understanding and data exploration** The dataset should be well used and all aspects of the data need to be considered to build the model, but first the data should be explored, the relationship between various variables need to be extracted to form an intuition.

## 2 Data Sets

The data is contained in three files:

- **portfolio.json** - containing offer ids and meta data about each offer (duration, type, etc.)
- **profile.json** - demographic data for each customer
- **transcript.json** - records for transactions, offers received, offers viewed, and offers completed

Here is the schema and explanation of each variable in the files:

**portfolio.json** \* id (string) - offer id \* offer\_type (string) - type of offer ie BOGO, discount, informational \* difficulty (int) - minimum required spend to complete an offer \* reward (int) - reward given for completing an offer \* duration (int) - time for offer to be open, in days \* channels (list of strings)

**profile.json** \* age (int) - age of the customer \* became\_member\_on (int) - date when customer created an app account \* gender (str) - gender of the customer (note some entries contain 'O' for other rather than M or F) \* id (str) - customer id \* income (float) - customer's income

**transcript.json** \* event (str) - record description (ie transaction, offer received, offer viewed, etc.) \* person (str) - customer id \* time (int) - time in hours since start of test. The data begins at time t=0 \* value - (dict of strings) - either an offer id or transaction amount depending on the record

**Note:** If you are using the workspace, you will need to go to the terminal and run the command `conda update pandas` before reading in the files. This is because the version of pandas in the workspace cannot read in the transcript.json file correctly, but the newest version of pandas can. You can access the terminal from the orange icon in the top left of this notebook.

You can see how to access the terminal and how the install works using the two images below. First you need to access the terminal:

Then you will want to run the above command:

Finally, when you enter back into the notebook (use the jupyter icon again), you should be able to run the below cell without any errors.

### DATA LOADING

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

```

import json
% matplotlib inline

# read in the json files
portfolio = pd.read_json('data/portfolio.json', orient='records', lines=True)
profile = pd.read_json('data/profile.json', orient='records', lines=True)
transcript = pd.read_json('data/transcript.json', orient='records', lines=True)

```

In [ ]:

In [ ]:

```

In [2]: from sklearn.preprocessing import OneHotEncoder, MultiLabelBinarizer
import matplotlib.pyplot as plt

import seaborn as sns

```

**DATA EXPLORATION** The below cells contain the exploration of data and an attempt has been made to analyse data and derive relation out of it using plots

In [3]: portfolio.head()

```

Out[3]:
   channels  difficulty  duration \
0  [email, mobile, social]      10      7
1  [web, email, mobile, social]    10      5
2  [web, email, mobile]           0      4
3  [web, email, mobile]           5      7
4  [web, email]                  20     10

   id      offer_type  reward
0  ae264e3637204a6fb9bb56bc8210ddfd      bogo      10
1  4d5c57ea9a6940dd891ad53e9dbe8da0      bogo      10
2  3f207df678b143eea3cee63160fa8bed  informational      0
3  9b98b8c7a33c4b65b9aebfe6a799e6d9      bogo      5
4  0b1e1539f2cc45b7b9fa7c272da2e1d7      discount      5

```

In [4]: portfolio.shape

Out[4]: (10, 6)

In [5]: profile.head()

```

Out[5]:
   age  became_member_on  gender  id  income
0  118      20170212    None  68be06ca386d4c31939f3a4f0e3dd783  NaN
1   55      20170715      F  0610b486422d4921ae7d2bf64640c50b  112000.0
2  118      20180712    None  38fe809add3b4fcf9315a9694bb96ff5  NaN
3   75      20170509      F  78afa995795e4d85b5d9ceeca43f5fef  100000.0
4  118      20170804    None  a03223e636434f42ac4c3df47e8bac43  NaN

```

```
In [6]: profile.shape
```

```
Out[6]: (17000, 5)
```

```
In [7]: transcript.head()
```

```
Out[7]:
```

	event	person	time	\
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	0	
1	offer received	a03223e636434f42ac4c3df47e8bac43	0	
2	offer received	e2127556f4f64592b11af22de27a7932	0	
3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	0	
4	offer received	68617ca6246f4fbc85e91a2a49552598	0	

	value
0	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}
1	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
2	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}
3	{'offer id': 'fafdc668e3743c1bb461111dcafc2a4'}
4	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}

```
In [8]: transcript.shape
```

```
Out[8]: (306534, 4)
```

```
In [9]: portfolio.dtypes,transcript.dtypes,profile.dtypes
```

```
Out[9]: (channels      object
difficulty    int64
duration      int64
id            object
offer_type    object
reward        int64
dtype: object, event      object
person        object
time          int64
value         object
dtype: object, age              int64
became_member_on      int64
gender                object
id                   object
income               float64
dtype: object)
```

```
In [ ]:
```

```
In [10]: portfolio['offer_type']
```

```
Out[10]: 0      bogo
         1      bogo
```

```

2    informational
3        bogo
4        discount
5        discount
6        discount
7    informational
8        bogo
9        discount
Name: offer_type, dtype: object

```

```
In [11]: data=pd.get_dummies(portfolio['offer_type'])
```

```
In [ ]:
```

```
In [12]: portfolio = pd.concat([portfolio,data],axis=1)
```

```
In [ ]:
```

```
In [13]: portfolio
```

```

Out[13]:
      channels  difficulty  duration \
0  [email, mobile, social]      10      7
1  [web, email, mobile, social]    10      5
2      [web, email, mobile]        0      4
3      [web, email, mobile]        5      7
4      [web, email]              20     10
5  [web, email, mobile, social]      7      7
6  [web, email, mobile, social]     10     10
7  [email, mobile, social]          0      3
8  [web, email, mobile, social]      5      5
9      [web, email, mobile]     10      7

      id      offer_type  reward  bogo  discount \
0  ae264e3637204a6fb9bb56bc8210ddfd      bogo    10      1      0
1  4d5c57ea9a6940dd891ad53e9dbe8da0      bogo    10      1      0
2  3f207df678b143eea3cee63160fa8bed  informational      0      0      0
3  9b98b8c7a33c4b65b9aebfe6a799e6d9      bogo      5      1      0
4  0b1e1539f2cc45b7b9fa7c272da2e1d7      discount      5      0      1
5  2298d6c36e964ae4a3e7e9706d1fb8c2      discount      3      0      1
6  fafdcd668e3743c1bb461111dcafc2a4      discount      2      0      1
7  5a8bc65990b245e5a138643cd4eb9837  informational      0      0      0
8  f19421c1d4aa40978ebb69ca19b0e20d      bogo      5      1      0
9  2906b810c7d4411798c6938adc9daaa5      discount      2      0      1

      informational
0              0
1              0
2              1
3              0

```

4	0
5	0
6	0
7	1
8	0
9	0

## DATA WRANGLING

```
In [14]: mlb = MultiLabelBinarizer() #channels column is exploited to break it into various columns
data1 = pd.DataFrame(mlb.fit_transform(portfolio['channels']),
                      columns=mlb.classes_,
                      index=portfolio['channels'].index)
```

```
In [15]: portfolio = portfolio.drop('channels', axis=1) # channels column is dropped and rest of the columns are added
portfolio = pd.concat([portfolio, data1], axis=1, sort=False)
```

```
In [16]: portfolio
```

```
Out[16]:
```

	difficulty	duration	id	offer_type
0	10	7	ae264e3637204a6fb9bb56bc8210ddfd	bogo
1	10	5	4d5c57ea9a6940dd891ad53e9dbe8da0	bogo
2	0	4	3f207df678b143eea3cee63160fa8bed	informational
3	5	7	9b98b8c7a33c4b65b9aebfe6a799e6d9	bogo
4	20	10	0b1e1539f2cc45b7b9fa7c272da2e1d7	discount
5	7	7	2298d6c36e964ae4a3e7e9706d1fb8c2	discount
6	10	10	fafdc668e3743c1bb461111dcafc2a4	discount
7	0	3	5a8bc65990b245e5a138643cd4eb9837	informational
8	5	5	f19421c1d4aa40978ebb69ca19b0e20d	bogo
9	10	7	2906b810c7d4411798c6938adc9daaa5	discount

	reward	bogo	discount	informational	email	mobile	social	web
0	10	1	0	0	1	1	1	0
1	10	1	0	0	1	1	1	1
2	0	0	0	1	1	1	0	1
3	5	1	0	0	1	1	0	1
4	5	0	1	0	1	0	0	1
5	3	0	1	0	1	1	1	1
6	2	0	1	0	1	1	1	1
7	0	0	0	1	1	1	1	0
8	5	1	0	0	1	1	1	1
9	2	0	1	0	1	1	0	1

```
In [17]: profile.isna().sum()
```

```
Out[17]: age                0
became_member_on          0
gender                  2175
id                      0
```

```

        income                2175
        dtype: int64

In [18]: profile['gender'].fillna('NA', inplace=True)
        profile['income']=profile['income'].fillna(profile['income'].mean())

In [19]: profile.isna().sum()

Out[19]: age                0
        became_member_on    0
        gender              0
        id                 0
        income              0
        dtype: int64

In [20]: transcript.isna().sum()

Out[20]: event            0
        person           0
        time             0
        value            0
        dtype: int64

In [21]: portfolio.isna().sum()

Out[21]: difficulty        0
        duration           0
        id                0
        offer_type         0
        reward             0
        bogo              0
        discount           0
        informational       0
        email             0
        mobile            0
        social            0
        web               0
        dtype: int64

In [22]: transcript.shape

Out[22]: (306534, 4)

In [23]: profile.shape

Out[23]: (17000, 5)

In [24]: transcript['value'][306510]

Out[24]: {'amount': 14.31}

```

```
In [25]: type_ = [] # a loop to extract different types of values in events column
        for idx, row in transcript.iterrows():
            for k in row['value']:
                if k in type_:
                    continue
                else:
                    type_.append(k)

        type_
```

```
Out[25]: ['offer id', 'amount', 'offer_id', 'reward']
```

```
In [26]: for idx, row in transcript.iterrows():
        print(row['value'])
        for k,i in row['value'].items():
            print(k)
            print(i)
            break
        break
```

```
{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}
offer id
9b98b8c7a33c4b65b9aebfe6a799e6d9
```

The values from value column in transcript is extracted and put into three columns for better analysis

```
In [27]: transcript['offer_id']=''
        transcript['reward']=0
        transcript['amount']=0
```

```
In [28]: transcript
```

```
Out[28]:
```

	event	person	time	\
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	0	
1	offer received	a03223e636434f42ac4c3df47e8bac43	0	
2	offer received	e2127556f4f64592b11af22de27a7932	0	
3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	0	
4	offer received	68617ca6246f4fbc85e91a2a49552598	0	
5	offer received	389bc3fa690240e798340f5a15918d5c	0	
6	offer received	c4863c7985cf408faee930f111475da3	0	
7	offer received	2eeac8d8feae4a8cad5a6af0499a211d	0	
8	offer received	aa4862eba776480b8bb9c68455b8c2e1	0	
9	offer received	31dda685af34476cad5bc968bdb01c53	0	
10	offer received	744d603ef08c4f33af5a61c8c7628d1c	0	
11	offer received	3d02345581554e81b7b289ab5e288078	0	
12	offer received	4b0da7e80e5945209a1fdddf813dbe0	0	
13	offer received	c27e0d6ab72c455a8bb66d980963de60	0	



14	offer received	d53717f5400c4e84affdaeda9dd926b3	0
15	offer received	f806632c011441378d4646567f357a21	0
16	offer received	d058f73bf8674a26a95227db098147b1	0
17	offer received	65aba5c617294649aeb624da249e1ee5	0
18	offer received	ebe7ef46ea6f4963a7dd49f501b26779	0
19	offer received	1e9420836d554513ab90eba98552d0a9	0
20	offer received	868317b9be554cb18e50bc68484749a2	0
21	offer received	f082d80f0aac47a99173ba8ef8fc1909	0
22	offer received	102e9454054946fda62242d2e176fdce	0
23	offer received	4beeb3ed64dd4898b0edf2f6b67426d3	0
24	offer received	9f30b375d7bd4c62a884ffe7034e09ee	0
25	offer received	25c906289d154b66bf579693f89481c9	0
26	offer received	6e014185620b49bd98749f728747572f	0
27	offer received	02c083884c7d45b39cc68e1314fec56c	0
28	offer received	c0d210398dee4a0895b24444a5fcd1d2	0
29	offer received	8be4463721e14d7fa600686bf8c8b2ed	0
...	...	...	...
306504	transaction	8524d450673b4c24869b6c94380006de	714
306505	transaction	b895c57e8cd047a8872ce02aa54759d6	714
306506	offer completed	b895c57e8cd047a8872ce02aa54759d6	714
306507	offer viewed	8dda575c2a1d44b9ac8e8b07b93d1f8e	714
306508	transaction	8431c16f8e1d440880db371a68f82dd0	714
306509	offer completed	8431c16f8e1d440880db371a68f82dd0	714
306510	transaction	ba620885e51c4b0ea64a4f61daad494f	714
306511	transaction	a1a8f40407c444cc848468275308958a	714
306512	transaction	8d80970192fa496f99d6b45c470a4b60	714
306513	transaction	bde275066f3c4fa0bff3093e3b866a2c	714
306514	transaction	f1e4fd36e5a0446f83861308bddf6945	714
306515	transaction	0b64be3b241c4407a5c9a71781173829	714
306516	transaction	86d03d35d7e0434b935e7743e83be3a0	714
306517	transaction	3408fd05c781401f8442fb6dbaaea9c7	714
306518	transaction	1593d617fac246ef8e50dbb0ffd77f5f	714
306519	transaction	f1b31d07b5d84f69a2d5f1d07843989e	714
306520	transaction	2ce987015ec0404a97ba333e8e814090	714
306521	transaction	2e33545f0a764d27b2ccff95fc8d72c4	714
306522	transaction	d1c4500ace2e45e9a45d3cd2fccac8d8	714
306523	transaction	b65affd9e07346a1906364a396950e3d	714
306524	transaction	d613ca9c59dd42f497bdfb6178da54a7	714
306525	transaction	eec70ab28af74a22a4aeb889c0317944	714
306526	transaction	24f56b5e1849462093931b164eb803b5	714
306527	offer completed	24f56b5e1849462093931b164eb803b5	714
306528	transaction	5ca2620962114246ab218fc648eb3934	714
306529	transaction	b3a1272bc9904337b331bf348c3e8c17	714
306530	transaction	68213b08d99a4ae1b0dcb72aebd9aa35	714
306531	transaction	a00058cf10334a308c68e7631c529907	714
306532	transaction	76ddbd6576844afe811f1a3c0fbb5bec	714
306533	transaction	c02b10e8752c4d8e9b73f918558531f7	714

		value	offer_id	reward	\
0	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}			0	
1	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}			0	
2	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}			0	
3	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}			0	
4	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}			0	
5	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}			0	
6	{'offer id': '2298d6c36e964ae4a3e7e9706d1fb8c2'}			0	
7	{'offer id': '3f207df678b143eea3cee63160fa8bed'}			0	
8	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}			0	
9	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}			0	
10	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}			0	
11	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}			0	
12	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}			0	
13	{'offer id': '3f207df678b143eea3cee63160fa8bed'}			0	
14	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}			0	
15	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}			0	
16	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}			0	
17	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}			0	
18	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}			0	
19	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}			0	
20	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}			0	
21	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}			0	
22	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}			0	
23	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}			0	
24	{'offer id': '2298d6c36e964ae4a3e7e9706d1fb8c2'}			0	
25	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}			0	
26	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}			0	
27	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}			0	
28	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}			0	
29	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}			0	
...		...	...	...	
306504		{'amount': 4.89}		0	
306505		{'amount': 4.48}		0	
306506	{'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...			0	
306507	{'offer_id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}			0	
306508		{'amount': 1.19}		0	
306509	{'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...			0	
306510		{'amount': 14.31}		0	
306511		{'amount': 2.37}		0	
306512		{'amount': 6.92}		0	
306513		{'amount': 12.73}		0	
306514		{'amount': 8.2}		0	
306515		{'amount': 2.6}		0	
306516		{'amount': 9.2}		0	
306517		{'amount': 11.7}		0	
306518		{'amount': 40.67}		0	
306519		{'amount': 31.13}		0	

306520	{ 'amount': 1.6400000000000001}	0
306521	{ 'amount': 17.35}	0
306522	{ 'amount': 4.42}	0
306523	{ 'amount': 18.35}	0
306524	{ 'amount': 25.14}	0
306525	{ 'amount': 43.58}	0
306526	{ 'amount': 22.64}	0
306527	{ 'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...	0
306528	{ 'amount': 2.2}	0
306529	{ 'amount': 1.5899999999999999}	0
306530	{ 'amount': 9.53}	0
306531	{ 'amount': 3.61}	0
306532	{ 'amount': 3.5300000000000002}	0
306533	{ 'amount': 4.05}	0

	amount
0	0
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0
11	0
12	0
13	0
14	0
15	0
16	0
17	0
18	0
19	0
20	0
21	0
22	0
23	0
24	0
25	0
26	0
27	0
28	0
29	0
...	...
306504	0

306505	0
306506	0
306507	0
306508	0
306509	0
306510	0
306511	0
306512	0
306513	0
306514	0
306515	0
306516	0
306517	0
306518	0
306519	0
306520	0
306521	0
306522	0
306523	0
306524	0
306525	0
306526	0
306527	0
306528	0
306529	0
306530	0
306531	0
306532	0
306533	0

[306534 rows x 7 columns]

```
In [29]: # Iterate over transcript table, check value column and update it, put each key in separate list
for idx, row in transcript.iterrows():
    for k_y, v_l in row['value'].items():
        if k_y == 'offer_id' or k_y == 'offer id':
            transcript.at[idx, 'offer_id'] = v_l
        if k_y == 'amount':
            transcript.at[idx, 'amount'] = v_l
        if k_y == 'reward':
            transcript.at[idx, 'reward'] = v_l
```

```
In [30]: transcript['offer_id'].loc[1]
```

```
Out[30]: '0b1e1539f2cc45b7b9fa7c272da2e1d7'
```

```
In [31]: transcript
```

Out [31]:

	event	person	time \
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	0
1	offer received	a03223e636434f42ac4c3df47e8bac43	0
2	offer received	e2127556f4f64592b11af22de27a7932	0
3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	0
4	offer received	68617ca6246f4fbc85e91a2a49552598	0
5	offer received	389bc3fa690240e798340f5a15918d5c	0
6	offer received	c4863c7985cf408faee930f111475da3	0
7	offer received	2eeac8d8feae4a8cad5a6af0499a211d	0
8	offer received	aa4862eba776480b8bb9c68455b8c2e1	0
9	offer received	31dda685af34476cad5bc968bdb01c53	0
10	offer received	744d603ef08c4f33af5a61c8c7628d1c	0
11	offer received	3d02345581554e81b7b289ab5e288078	0
12	offer received	4b0da7e80e5945209a1fdddfe813dbe0	0
13	offer received	c27e0d6ab72c455a8bb66d980963de60	0
14	offer received	d53717f5400c4e84affdaeda9dd926b3	0
15	offer received	f806632c011441378d4646567f357a21	0
16	offer received	d058f73bf8674a26a95227db098147b1	0
17	offer received	65aba5c617294649aeb624da249e1ee5	0
18	offer received	ebe7ef46ea6f4963a7dd49f501b26779	0
19	offer received	1e9420836d554513ab90eba98552d0a9	0
20	offer received	868317b9be554cb18e50bc68484749a2	0
21	offer received	f082d80f0aac47a99173ba8ef8fc1909	0
22	offer received	102e9454054946fda62242d2e176fdce	0
23	offer received	4beeb3ed64dd4898b0edf2f6b67426d3	0
24	offer received	9f30b375d7bd4c62a884ffe7034e09ee	0
25	offer received	25c906289d154b66bf579693f89481c9	0
26	offer received	6e014185620b49bd98749f728747572f	0
27	offer received	02c083884c7d45b39cc68e1314fec56c	0
28	offer received	c0d210398dee4a0895b24444a5fcd1d2	0
29	offer received	8be4463721e14d7fa600686bf8c8b2ed	0
...	...	...	...
306504	transaction	8524d450673b4c24869b6c94380006de	714
306505	transaction	b895c57e8cd047a8872ce02aa54759d6	714
306506	offer completed	b895c57e8cd047a8872ce02aa54759d6	714
306507	offer viewed	8dda575c2a1d44b9ac8e8b07b93d1f8e	714
306508	transaction	8431c16f8e1d440880db371a68f82dd0	714
306509	offer completed	8431c16f8e1d440880db371a68f82dd0	714
306510	transaction	ba620885e51c4b0ea64a4f61daad494f	714
306511	transaction	a1a8f40407c444cc848468275308958a	714
306512	transaction	8d80970192fa496f99d6b45c470a4b60	714
306513	transaction	bde275066f3c4fa0bff3093e3b866a2c	714
306514	transaction	f1e4fd36e5a0446f83861308bddf6945	714
306515	transaction	0b64be3b241c4407a5c9a71781173829	714
306516	transaction	86d03d35d7e0434b935e7743e83be3a0	714
306517	transaction	3408fd05c781401f8442fb6dba9c7	714
306518	transaction	1593d617fac246ef8e50dbb0ffd77f5f	714
306519	transaction	f1b31d07b5d84f69a2d5f1d07843989e	714

306520	transaction	2ce987015ec0404a97ba333e8e814090	714
306521	transaction	2e33545f0a764d27b2ccff95fc8d72c4	714
306522	transaction	d1c4500ace2e45e9a45d3cd2fccac8d8	714
306523	transaction	b65affd9e07346a1906364a396950e3d	714
306524	transaction	d613ca9c59dd42f497bdbf6178da54a7	714
306525	transaction	eec70ab28af74a22a4aeb889c0317944	714
306526	transaction	24f56b5e1849462093931b164eb803b5	714
306527	offer completed	24f56b5e1849462093931b164eb803b5	714
306528	transaction	5ca2620962114246ab218fc648eb3934	714
306529	transaction	b3a1272bc9904337b331bf348c3e8c17	714
306530	transaction	68213b08d99a4ae1b0dcb72aebd9aa35	714
306531	transaction	a00058cf10334a308c68e7631c529907	714
306532	transaction	76ddb6576844afe811f1a3c0fbb5bec	714
306533	transaction	c02b10e8752c4d8e9b73f918558531f7	714

		value \
0	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	
1	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
2	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	
3	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}	
4	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}	
5	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}	
6	{'offer id': '2298d6c36e964ae4a3e7e9706d1fb8c2'}	
7	{'offer id': '3f207df678b143eea3cee63160fa8bed'}	
8	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
9	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
10	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
11	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
12	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}	
13	{'offer id': '3f207df678b143eea3cee63160fa8bed'}	
14	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
15	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}	
16	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
17	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	
18	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	
19	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}	
20	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	
21	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	
22	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}	
23	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	
24	{'offer id': '2298d6c36e964ae4a3e7e9706d1fb8c2'}	
25	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	
26	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}	
27	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}	
28	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	
29	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}	
...		...
306504		{'amount': 4.89}

```

306505                                     {'amount': 4.48}
306506 {'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...
306507   {'offer_id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
306508                                     {'amount': 1.19}
306509 {'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...
306510                                     {'amount': 14.31}
306511                                     {'amount': 2.37}
306512                                     {'amount': 6.92}
306513                                     {'amount': 12.73}
306514                                     {'amount': 8.2}
306515                                     {'amount': 2.6}
306516                                     {'amount': 9.2}
306517                                     {'amount': 11.7}
306518                                     {'amount': 40.67}
306519                                     {'amount': 31.13}
306520                                     {'amount': 1.6400000000000001}
306521                                     {'amount': 17.35}
306522                                     {'amount': 4.42}
306523                                     {'amount': 18.35}
306524                                     {'amount': 25.14}
306525                                     {'amount': 43.58}
306526                                     {'amount': 22.64}
306527 {'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...
306528                                     {'amount': 2.2}
306529                                     {'amount': 1.5899999999999999}
306530                                     {'amount': 9.53}
306531                                     {'amount': 3.61}
306532                                     {'amount': 3.5300000000000002}
306533                                     {'amount': 4.05}

```

	offer_id	reward	amount
0	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0
1	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0
2	2906b810c7d4411798c6938adc9daaa5	0	0
3	fafdcd668e3743c1bb461111dcafc2a4	0	0
4	4d5c57ea9a6940dd891ad53e9dbe8da0	0	0
5	f19421c1d4aa40978ebb69ca19b0e20d	0	0
6	2298d6c36e964ae4a3e7e9706d1fb8c2	0	0
7	3f207df678b143eea3cee63160fa8bed	0	0
8	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0
9	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0
10	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0
11	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0
12	ae264e3637204a6fb9bb56bc8210ddfd	0	0
13	3f207df678b143eea3cee63160fa8bed	0	0
14	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0
15	fafdcd668e3743c1bb461111dcafc2a4	0	0
16	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0

17	2906b810c7d4411798c6938adc9daaa5	0	0
18	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0
19	ae264e3637204a6fb9bb56bc8210ddfd	0	0
20	2906b810c7d4411798c6938adc9daaa5	0	0
21	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0
22	4d5c57ea9a6940dd891ad53e9dbe8da0	0	0
23	2906b810c7d4411798c6938adc9daaa5	0	0
24	2298d6c36e964ae4a3e7e9706d1fb8c2	0	0
25	2906b810c7d4411798c6938adc9daaa5	0	0
26	f19421c1d4aa40978ebb69ca19b0e20d	0	0
27	ae264e3637204a6fb9bb56bc8210ddfd	0	0
28	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0
29	fafdc668e3743c1bb461111dcafc2a4	0	0
...	...	...	...
306504		0	4
306505		0	4
306506	fafdc668e3743c1bb461111dcafc2a4	2	0
306507	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0
306508		0	1
306509	fafdc668e3743c1bb461111dcafc2a4	2	0
306510		0	14
306511		0	2
306512		0	6
306513		0	12
306514		0	8
306515		0	2
306516		0	9
306517		0	11
306518		0	40
306519		0	31
306520		0	1
306521		0	17
306522		0	4
306523		0	18
306524		0	25
306525		0	43
306526		0	22
306527	fafdc668e3743c1bb461111dcafc2a4	2	0
306528		0	2
306529		0	1
306530		0	9
306531		0	3
306532		0	3
306533		0	4

[306534 rows x 7 columns]

In [32]: transcript.loc[306528]



```

Out [32]: event                                transaction
          person      5ca2620962114246ab218fc648eb3934
          time                                714
          value                                {'amount': 2.2}
          offer_id
          reward                                0
          amount                                2
          Name: 306528, dtype: object

```

```

In [33]: trans=transcript.drop('value',axis=1)

```

```

In [34]: trans.head()

```

```

Out [34]:
          event                                person  time  \
0  offer received  78afa995795e4d85b5d9ceeca43f5fef    0
1  offer received  a03223e636434f42ac4c3df47e8bac43    0
2  offer received  e2127556f4f64592b11af22de27a7932    0
3  offer received  8ec6ce2a7e7949b1bf142def7d0e0586    0
4  offer received  68617ca6246f4fbc85e91a2a49552598    0

          offer_id  reward  amount
0  9b98b8c7a33c4b65b9aebfe6a799e6d9      0      0
1  0b1e1539f2cc45b7b9fa7c272da2e1d7      0      0
2  2906b810c7d4411798c6938adc9daaa5      0      0
3  fafdcd668e3743c1bb461111dcafc2a4      0      0
4  4d5c57ea9a6940dd891ad53e9dbe8da0      0      0

```

```

In [35]: trans['time']

```

```

Out [35]: 0      0
          1      0
          2      0
          3      0
          4      0
          5      0
          6      0
          7      0
          8      0
          9      0
         10      0
         11      0
         12      0
         13      0
         14      0
         15      0
         16      0
         17      0
         18      0
         19      0

```

```

20      0
21      0
22      0
23      0
24      0
25      0
26      0
27      0
28      0
29      0

```

```

...
306504    714
306505    714
306506    714
306507    714
306508    714
306509    714
306510    714
306511    714
306512    714
306513    714
306514    714
306515    714
306516    714
306517    714
306518    714
306519    714
306520    714
306521    714
306522    714
306523    714
306524    714
306525    714
306526    714
306527    714
306528    714
306529    714
306530    714
306531    714
306532    714
306533    714

```

Name: time, Length: 306534, dtype: int64

In [36]: profile.describe()

```

Out[36]:
count    17000.000000    age    62.531412    became_member_on    1.700000e+04    income    17000.000000
mean      62.531412      2.016703e+07    65404.991568

```

std	26.738580	1.167750e+04	20169.288288
min	18.000000	2.013073e+07	30000.000000
25%	45.000000	2.016053e+07	51000.000000
50%	58.000000	2.017080e+07	65404.991568
75%	73.000000	2.017123e+07	76000.000000
max	118.000000	2.018073e+07	120000.000000

In [37]: trans.describe()

Out [37]:

	time	reward	amount
count	306534.000000	306534.000000	306534.000000
mean	366.382940	0.537219	5.570133
std	200.326314	1.805208	21.266669
min	0.000000	0.000000	0.000000
25%	186.000000	0.000000	0.000000
50%	408.000000	0.000000	0.000000
75%	528.000000	0.000000	7.000000
max	714.000000	10.000000	1062.000000

In [38]: portfolio.describe()

Out [38]:

	difficulty	duration	reward	bogo	discount	informational \
count	10.000000	10.000000	10.000000	10.000000	10.000000	10.000000
mean	7.700000	6.500000	4.200000	0.400000	0.400000	0.200000
std	5.831905	2.321398	3.583915	0.516398	0.516398	0.421637
min	0.000000	3.000000	0.000000	0.000000	0.000000	0.000000
25%	5.000000	5.000000	2.000000	0.000000	0.000000	0.000000
50%	8.500000	7.000000	4.000000	0.000000	0.000000	0.000000
75%	10.000000	7.000000	5.000000	1.000000	1.000000	0.000000
max	20.000000	10.000000	10.000000	1.000000	1.000000	1.000000

	email	mobile	social	web
count	10.0	10.000000	10.000000	10.000000
mean	1.0	0.900000	0.600000	0.800000
std	0.0	0.316228	0.516398	0.421637
min	1.0	0.000000	0.000000	0.000000
25%	1.0	1.000000	0.000000	1.000000
50%	1.0	1.000000	1.000000	1.000000
75%	1.0	1.000000	1.000000	1.000000
max	1.0	1.000000	1.000000	1.000000

**ANALYZING DATA** In the following cells usage of plots has been made to understand the data as well as visualize the data and thus answer some of the questions

Q1 How is the data distributed in various columns? Q2 What is the average income for the customers? Q3 What is the age age of Starbucks customers> Q4 What are the various types of offers being laid out? Q5 What is the distribution of these offers? Q6 How were the offers received, viewed and completed? Q7 Which offer\_id is connected to which offer type? Q8 For all the unique customers how much amount do they spend and who all are the loyal customers? Q9 what is the

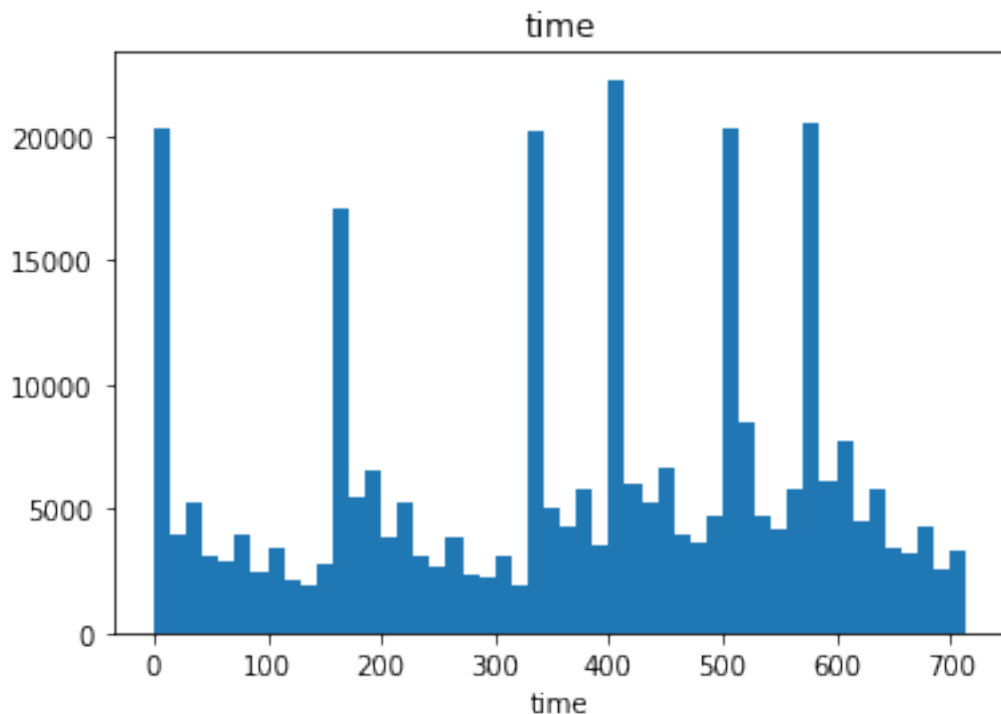
distribution of events in transcript? Q10 What is the most common promotion among various age groups? Q11 how are the people among various genders taking these offers and how effective the offers are?

**Q1) How is the data distributed in various columns?** The distribution of variables in columns is exploited to extract relationship among them.

```
In [39]: plt.hist(trans['time'],bins=50)
          plt.xlabel("time")

          plt.title("time")
          plt
```

```
Out[39]: <module 'matplotlib.pyplot' from '/opt/conda/lib/python3.6/site-packages/matplotlib/pyplot.py'>
```



```
In [ ]:
```

```
In [40]: profile.columns
```

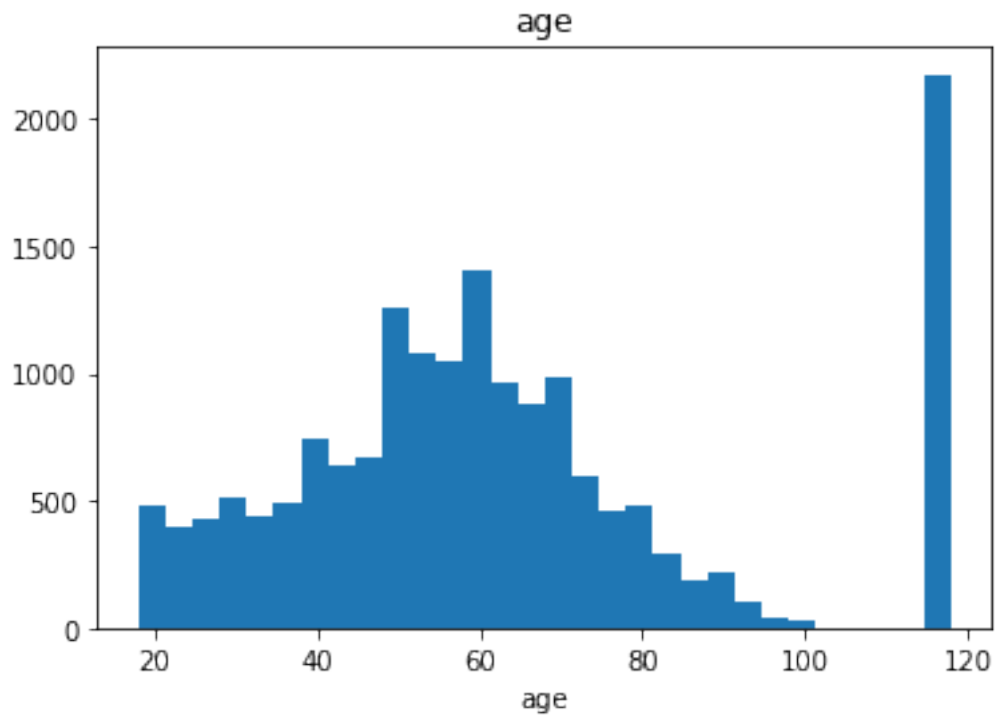
```
Out[40]: Index(['age', 'became_member_on', 'gender', 'id', 'income'], dtype='object')
```

The graph shows histogram plot for age in profile dataset

```
In [41]: plt.hist(profile['age'],bins=30)
plt.xlabel("age")

plt.title("age")
```

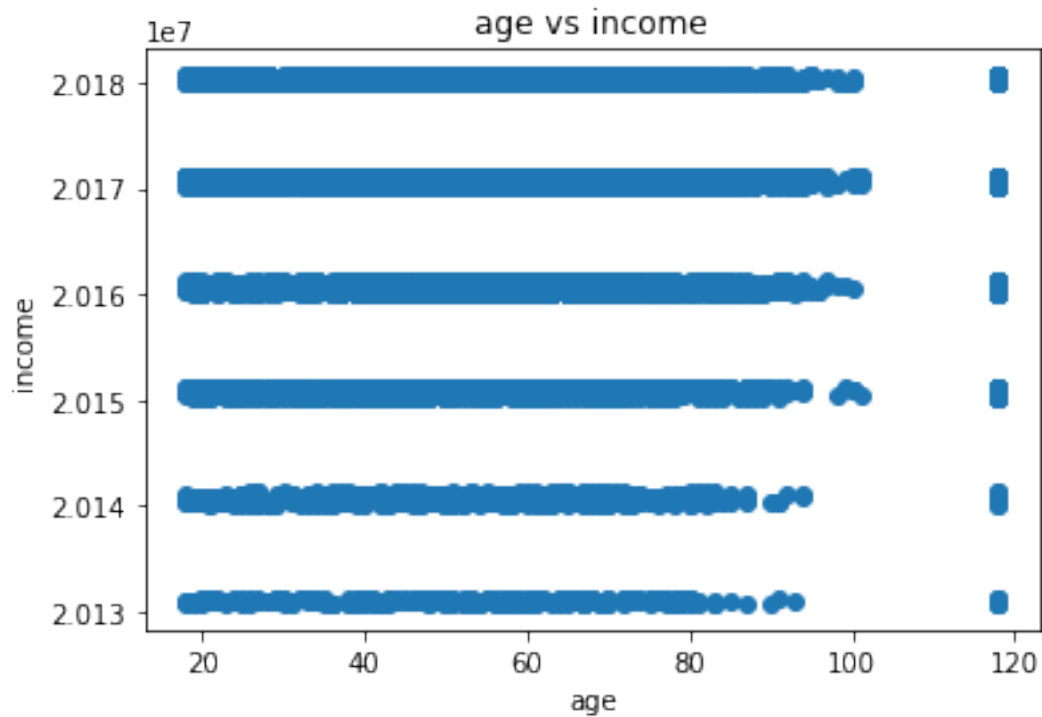
```
Out[41]: Text(0.5,1,'age')
```



The graph shows scatter plot for income vs age in profile dataset

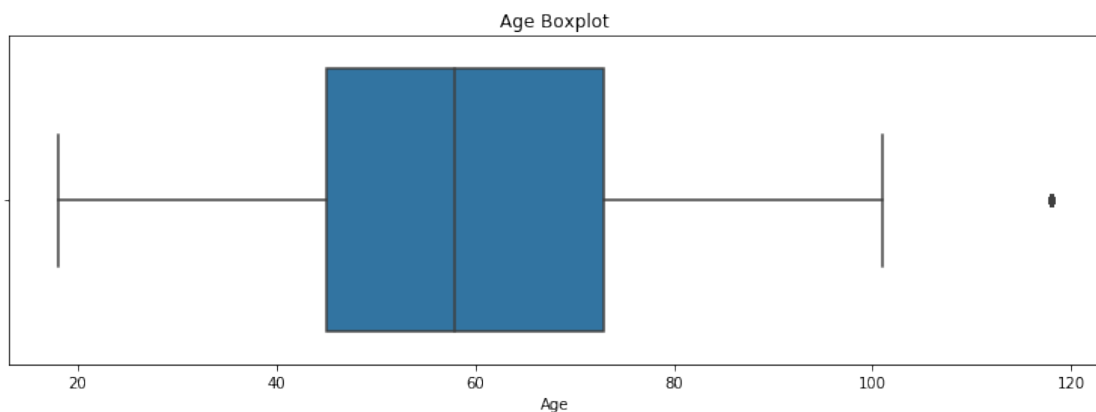
```
In [42]: plt.scatter(profile['age'],profile['became_member_on'])
plt.xlabel("age")
plt.ylabel("income")
plt.title("age vs income")
```

```
Out[42]: Text(0.5,1,'age vs income')
```



The graph shows box plot for income in pofile dataset

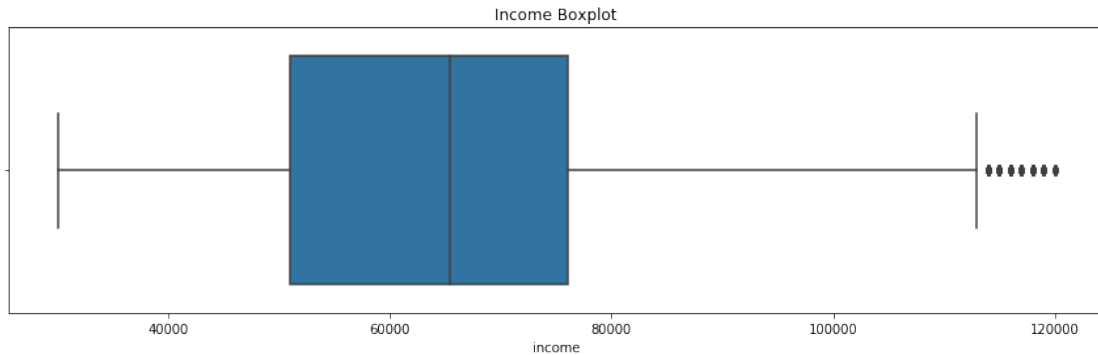
```
In [43]: plt.figure(figsize=(13, 4))
sns.boxplot(profile['age'])
plt.title('Age Boxplot')
plt.xlabel('Age')
plt.xticks(rotation = 0)
plt.show();
```



Here we can see an outlier in the graph

The graph shows box plot for income in pofile dataset

```
In [44]: plt.figure(figsize=(15,4))
sns.boxplot(profile["income"])
plt.title('Income Boxplot')
plt.xlabel('income')
plt.xticks(rotation = 0)
plt.show();
```



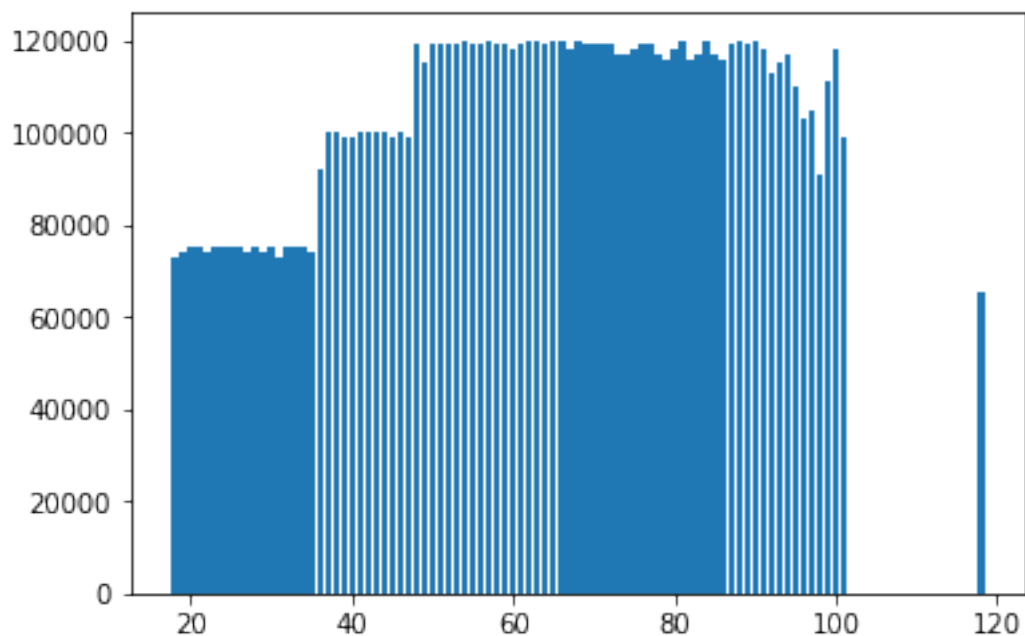
Here again we can see outlier in the graph for distribution of income

```
In [ ]:
```

The following graph shows the distribution of age and income in profile dataset

```
In [45]: plt.bar(profile['age'],profile['income'])
```

```
Out[45]: <Container object of 17000 artists>
```



```
In [46]: count_age = profile['age'].value_counts()
```

```
In [47]: count_age.shape
```

```
Out[47]: (85,)
```

This shows 85 different values in age column

```
In [48]: profile['age'].describe()
```

```
Out[48]: count      17000.000000
         mean        62.531412
         std         26.738580
         min         18.000000
         25%         45.000000
         50%         58.000000
         75%         73.000000
         max         118.000000
         Name: age, dtype: float64
```

The following distributes the age column in different age categories

```
In [49]: profile['age_by_decade'] = pd.cut(x=profile['age'], bins=[10,19, 29, 39, 49,59,69,79,89,99])
```

```
In [50]: profile['age_by_decade']
```

```
Out[50]: 0      110s
         1       50s
         2      110s
         3       70s
         4      110s
         5       60s
         6      110s
         7      110s
         8       60s
         9      110s
        10      110s
        11      110s
        12       50s
        13       60s
        14       20s
        15       60s
        16       40s
        17      110s
        18       50s
        19       60s
```



20	40s
21	60s
22	70s
23	110s
24	40s
25	50s
26	110s
27	30s
28	40s
29	50s
...	
16970	60s
16971	50s
16972	40s
16973	30s
16974	50s
16975	60s
16976	30s
16977	110s
16978	20s
16979	60s
16980	110s
16981	80s
16982	110s
16983	70s
16984	70s
16985	20s
16986	50s
16987	50s
16988	60s
16989	110s
16990	70s
16991	110s
16992	20s
16993	60s
16994	110s
16995	40s
16996	60s
16997	40s
16998	80s
16999	60s

Name: age\_by\_decade, Length: 17000, dtype: category  
Categories (11, object): [10s < 20s < 30s < 40s ... 80s < 90s < 100s < 110s]

```
In [51]: max_count_ages = profile['age'].value_counts()[1:].head(20).reset_index()
```

```
In [52]: max_count_ages['index']
```

```
Out[52]: 0      58
```

```

1    53
2    51
3    54
4    59
5    57
6    52
7    55
8    56
9    63
10   60
11   49
12   62
13   67
14   64
15   61
16   48
17   50
18   66
19   65
Name: index, dtype: int64

```

Age number for the customers we are leaving the first column with age 118

```

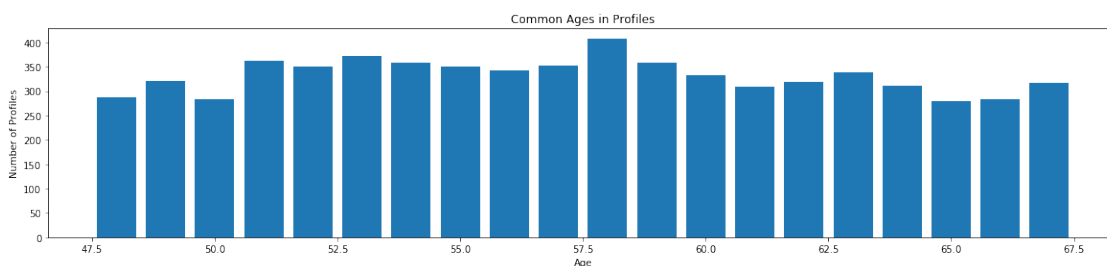
In [53]: plt.figure(figsize=(20,4))
plt.bar(max_count_ages['index'],max_count_ages['age'])
plt.title('Common Ages in Profiles')
plt.ylabel('Number of Profiles')
plt.xlabel('Age')

```

```

Out[53]: Text(0.5,0, 'Age')

```

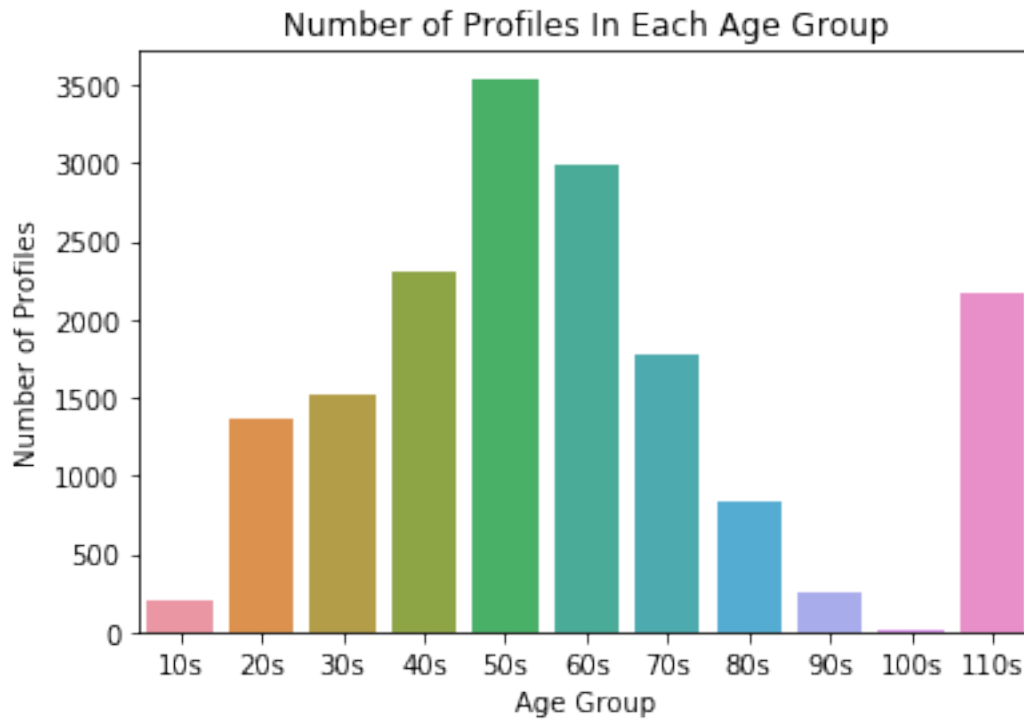


Here we can see that the common age group acting as out biggest customer is 50

```

In [54]: sns.countplot(x=profile['age_by_decade'])
plt.title('Number of Profiles In Each Age Group')
plt.ylabel('Number of Profiles')
plt.xlabel('Age Group')
plt.show();

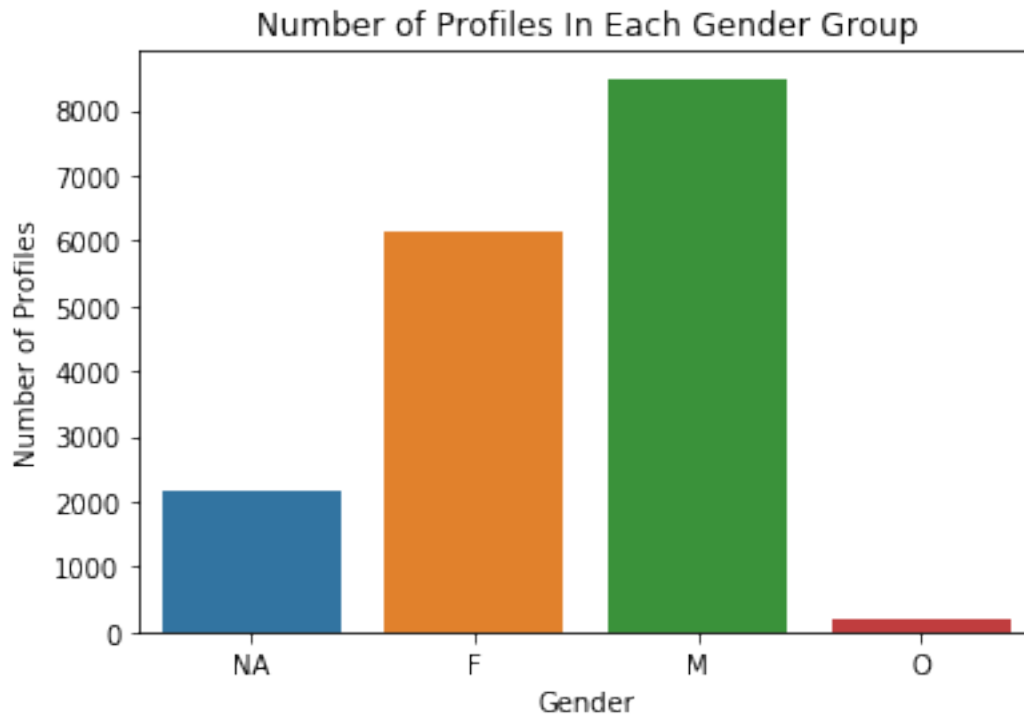
```



In [ ]:

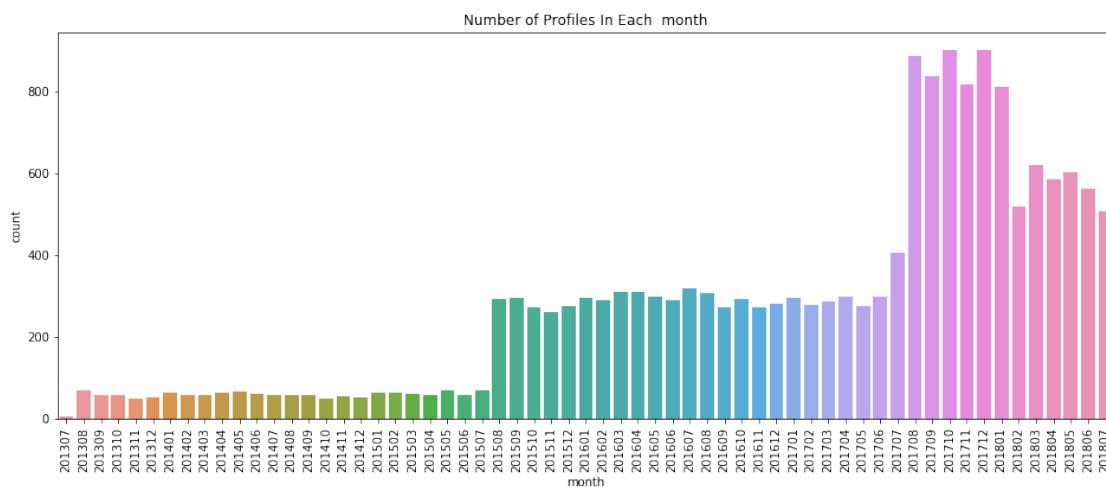
Male are buying more than male and a good portion of database contains 'NA'

```
In [55]: sns.countplot(x=profile['gender'])  
plt.title('Number of Profiles In Each Gender Group')  
plt.ylabel('Number of Profiles')  
plt.xlabel('Gender')  
plt.show();
```



```
In [56]: profile['profile_per_month']=profile['became_member_on'].astype(str).str[:6]
```

```
In [57]: plt.figure(figsize=(16, 6))
sns.countplot(x=profile['profile_per_month'])
plt.title('Number of Profiles In Each month')
plt.xlabel('month')
plt.xticks(rotation=90)
plt.show();
```



```
In [58]: transcript.head()
```

```
Out[58]:
```

	event	person	time	\
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	0	
1	offer received	a03223e636434f42ac4c3df47e8bac43	0	
2	offer received	e2127556f4f64592b11af22de27a7932	0	
3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	0	
4	offer received	68617ca6246f4fbc85e91a2a49552598	0	

	value	\
0	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	
1	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
2	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	
3	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}	
4	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}	

	offer_id	reward	amount
0	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0
1	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0
2	2906b810c7d4411798c6938adc9daaa5	0	0
3	fafdcd668e3743c1bb461111dcafc2a4	0	0
4	4d5c57ea9a6940dd891ad53e9dbe8da0	0	0

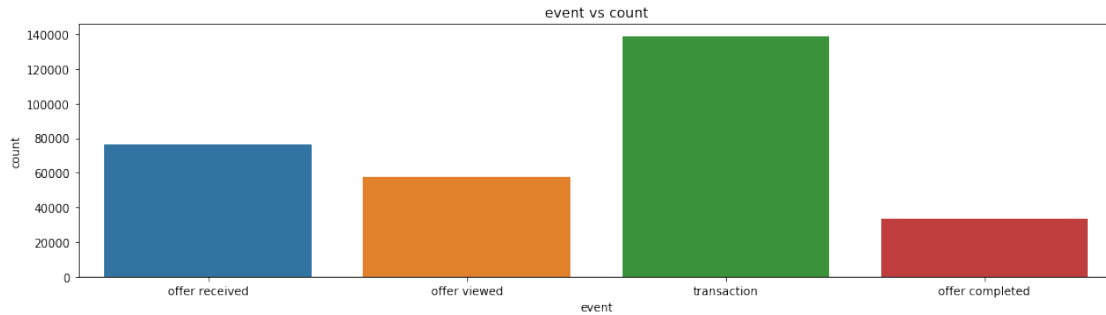
We can see an increase in count in 2017 october and 2017 december

```
In [59]: transcript['event'].value_counts()
```

```
Out[59]: transaction      138953
offer received           76277
offer viewed             57725
offer completed          33579
Name: event, dtype: int64
```

```
In [60]: plt.figure(figsize=(16,4))
sns.countplot(x=transcript['event'])
plt.title("event vs count")
plt.xlabel("event")
plt.ylabel("count")
```

```
Out[60]: Text(0,0.5,'count')
```



Here we can see that most people go for transaction and there is a good amount of people who view and don't make use of the offer and some people make use of the offers

```
In [61]: transcript['person'].value_counts()
```

```
Out[61]: 94de646f7b6041228ca7dec82adb97d2    51
          8dbfa485249f409aa223a2130f40634a    49
          5e60c6aa3b834e44b822ea43a3efea26    48
          79d9d4f86aca4bed9290350fb43817c2    48
          d0a80415b84c4df4908b8403b19765e3    48
          bd2cdd691aca4bb0a0e039979ee5de5c    46
          28681c16026943e68f26feaccab0907f    46
          a42ed50acc4d4b25bca647c9e0b916ad    46
          b1f4ece7d49342628a9ed77aee2cde58    46
          ab25fd6fbd5040f880751921e4029757    44
          9ae56116908640fc83477982da0aaec4    43
          d087fd0166404163b7d1e1e7cf2a9ac7    43
          ca265792e65949d79b2b0e91bdd31c57    43
          86e9d338b85b4177b369fe6b0ad4fed3    43
          4142f5e23db741b1af4be0287dc91c1c    43
          0ebc3c4c39234ab6a2701fe2525705a9    42
          cd9bac9e8aea4609929a55b9b468c88e    42
          edc7b04392144da9979f3077095f268a    42
          8e7d398d4bd948e397e201ad2bd5cce8    42
          40ce078d5b2a43d19138a788754520be    42
          0d74b166a5e54b269795dbaf38c6dfae    42
          5da599f0f0ca40a6916e28487a55e655    41
          1d755c218f714559a57ee7df7e6b1ca0    41
          f0a3a3c05e3c4e2e84929a49a6b5488c    41
          2ddc7d63c32d4606a7a45e3e70439b44    41
          a6fce370a2ce4df995fc4899bfeb3b6a    41
          6cd32ababc644c6c8a2644368c795728    41
          562b9efc809b4bd897ce0381347aaea2    41
          417c8e42cba54dd0ba1ea7ee079ef87a    41
          81a263ee0b8544b6a8910ee690cc6edd    41
```

...

```

c6e579c6821c41d1a7a6a9cf936e91bb    4
0a9fe790648c471bb8ee7bd554ce3122    4
11e2d9f6ef474d13bcf1db21f5c7bb62    4
1b978feee51d4afe83ecde1ae78907cc    3
d727102ac242449ab15f1bd1af28e6ff    3
fafcd6ee168140fbbb5da43be1d3daa7    3
76341c0cc6684b3eb23661e195dfc9a3    3
19a0510b9ce24b9da44618f7161ae72d    3
50f26d1787444bb6a1e1b8be501f6877    3
83abd8407034461782483fb32d3d5f5c    3
ce1579c557c14f7785869dc80638bc0f    3
12ede229379747bd8d74ccdc20097ca3    3
bc0c484263b94b0896f20c5e4fdf3585    3
08e7c2a166ff44e4a009a18b5e8e4b81    3
3a4874d8f0ef42b9a1b72294902afea9    3
f67a6524092d48a788a415c453bd2e00    3
af63cf0ed6ad4c458a03cb321927b463    3
2e9660f6e83b49bbb9d533b9317359c4    3
3045af4e98794a04a5542d3eac939b1f    2
1bfe13d2453c4185a6486c6817e0d568    2
22617705eec442e0b7b43e5c5f56fb17    2
cae5e211053f4121a389a7da4d631f7f    2
3a4e53046c544134bb1e7782248631d1    2
fccc9279ba56411f80ffe8ce7e0935cd    2
912b9f623b9e4b4eb99b6dc919f09a93    2
df9fc9a86ca84ef5aedde8925d5838ba    2
afd41b230f924f9ca8f5ed6249616114    2
e63e42480aae4ede9f07cac49c8c3f78    2
7ecfc592171f4844bdc05bdbb48d3847    2
da7a7c0dcfcb41a8acc7864a53cf60fb    1
Name: person, Length: 17000, dtype: int64

```

## Q2 Average income for starbucks customer

```
In [62]: profile['income'].mean()
```

```
Out[62]: 65404.991568296799
```

## Q3 Average age of the customers

```
In [63]: profile['age'].describe()['mean']
```

```
Out[63]: 62.531411764705879
```

## Q4 Various types of offers being laid out

```
In [64]: transcript['offer_id'].value_counts()
```

```
Out [64]:
```

fafdc668e3743c1bb461111dcafc2a4	138953
2298d6c36e964ae4a3e7e9706d1fb8c2	20241
f19421c1d4aa40978ebb69ca19b0e20d	20139
4d5c57ea9a6940dd891ad53e9dbe8da0	19131
ae264e3637204a6fb9bb56bc8210ddfd	18222
9b98b8c7a33c4b65b9aebfe6a799e6d9	18062
2906b810c7d4411798c6938adc9daaa5	16202
5a8bc65990b245e5a138643cd4eb9837	15767
0b1e1539f2cc45b7b9fa7c272da2e1d7	14305
3f207df678b143eea3cee63160fa8bed	13751
	11761

```
Name: offer_id, dtype: int64
```

```
In [65]: transcript['offer_id'].value_counts().index.tolist()
```

```
Out [65]: ['',
            'fafdc668e3743c1bb461111dcafc2a4',
            '2298d6c36e964ae4a3e7e9706d1fb8c2',
            'f19421c1d4aa40978ebb69ca19b0e20d',
            '4d5c57ea9a6940dd891ad53e9dbe8da0',
            'ae264e3637204a6fb9bb56bc8210ddfd',
            '9b98b8c7a33c4b65b9aebfe6a799e6d9',
            '2906b810c7d4411798c6938adc9daaa5',
            '5a8bc65990b245e5a138643cd4eb9837',
            '0b1e1539f2cc45b7b9fa7c272da2e1d7',
            '3f207df678b143eea3cee63160fa8bed']
```

```
In [66]: transcript['offer_id'].dtype
```

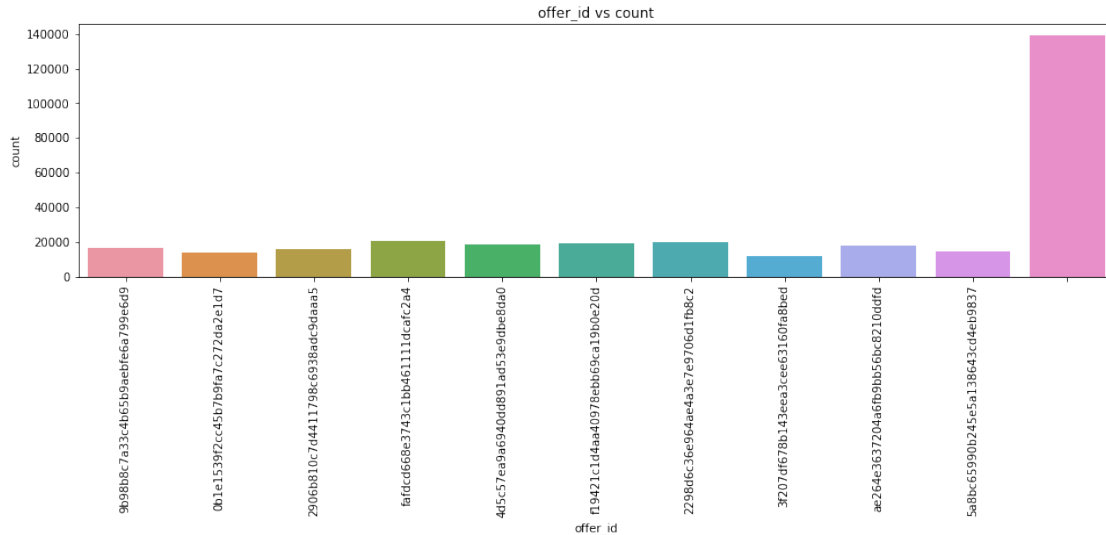
```
Out [66]: dtype('O')
```

### Q5 Distribution of these offers

```
In [67]: plt.figure(figsize=(16,4))
sns.countplot(x=transcript['offer_id'])
plt.title("offer_id vs count")
plt.xlabel("offer_id")
plt.ylabel("count")
plt.xticks(rotation=90)
```

```
Out [67]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10]),
  <a list of 11 Text xticklabel objects>)
```





This shows the most columns dont have offer id

```
In [68]: transcript.columns
```

```
Out[68]: Index(['event', 'person', 'time', 'value', 'offer_id', 'reward', 'amount'], dtype='object')
```

```
In [69]: id_offer = transcript['offer_id'].value_counts().index.tolist()[1:]
```

```
In [70]: transcript['event'].value_counts()
```

```
Out[70]: transaction      138953
offer received      76277
offer viewed      57725
offer completed      33579
Name: event, dtype: int64
```

```
In [71]: offer_type=transcript['event'].value_counts().index.tolist()
offer_type
```

```
Out[71]: ['transaction', 'offer received', 'offer viewed', 'offer completed']
```

```
In [72]: transcript['event'][transcript['offer_id']=='afdc668e3743c1bb461111dcafc2a4'].value_c
```

```
Out[72]: 7597
```

```
In [73]: new_df=pd.DataFrame(id_offer)
```

```
In [74]: new = pd.DataFrame(columns=['transaction', 'offer_received', 'offer_viewed', 'offer_com
new_df.join(new)
```

```
In [75]: new_df=new_df.join(new)
```

```
In [76]: new_df.columns
```

```
Out[76]: Index([0, 'transaction', 'offer_received', 'offer_viewed', 'offer_completed'], dtype='object')
```

**Q6 Distribution of offers into received viewd and completed and how many times transaction was done?** A new dataframe is created to view the distribution

```
In [77]: def get_count_offer_received():
    '''
    Input
    Though not explicitly taken but the input is transcript['event']
    Output
    Classification of all the offers based on the no of times they were received by cust
    '''
    o=0
    for i in id_offer:
        new_df.offer_received[o]=transcript['event'][transcript['offer_id']==i].value_c
        print(transcript['event'][transcript['offer_id']==i].value_counts()['offer rece
        o=o+1
```

```
In [78]: get_count_offer_received()
```

```
7597
7646
7571
7593
7658
7677
7632
7618
7668
7617
```

```
In [79]: def get_count_transaction():
    '''
    Input
    Though not explicitly taken but the input is transcript['event']
    Output
    Classification of all the offers based on the no of times transaction was done
    '''
    o=0
    for i in id_offer:
        try:
            new_df.transaction[o]=transcript['event'][transcript['offer_id']==i].value_
            o=o+1
        except:
            new_df.transaction[o]=0
            o=o+1
```

```
In [80]: get_count_transaction()
```

```
In [ ]:
```

```
In [83]: def get_count_offer_viewed():
```

```
    '''
```

```
    Input
```

```
    Though not explicitly taken but the input is transcript['event']
```

```
    Output
```

```
    Classification of all the offers based on the no of times they were viewed by custom
```

```
    '''
```

```
    o=0
```

```
    for i in id_offer:
```

```
        new_df.offer_viewed[o]=transcript['event'][transcript['offer_id']==i].value_cou
```

```
        print(transcript['event'][transcript['offer_id']==i].value_counts()['offer rece
```

```
        o=o+1
```

```
In [87]: get_count_offer_viewed()
```

```
7597
```

```
7646
```

```
7571
```

```
7593
```

```
7658
```

```
7677
```

```
7632
```

```
7618
```

```
7668
```

```
7617
```

```
In [88]: def get_count_offer_completed():
```

```
    '''
```

```
    Input
```

```
    Though not explicitly taken but the input is transcript['event']
```

```
    Output
```

```
    Classification of all the offers based on the no of times they were completed by cus
```

```
    '''
```

```
    o=0
```

```
    for i in id_offer:
```

```
        try:
```

```
            new_df.offer_completed[o]=transcript['event'][transcript['offer_id']==i].va
```

```
            o=o+1
```

```
        except:
```

```
            new_df.offer_completed[o]=0
```

```
            o=o+1
```

```
        #print(transcript['event'][transcript['offer_id']==i].value_counts()['offer rec
```

```
In [89]: get_count_offer_completed()
```

```
In [90]: new_df
```

```
Out[90]:
```

		0	transaction	offer_received	offer_viewed	\
0	fafdc668e3743c1bb461111dcafc2a4	0		7597	7327	
1	2298d6c36e964ae4a3e7e9706d1fb8c2	0		7646	7337	
2	f19421c1d4aa40978ebb69ca19b0e20d	0		7571	7264	
3	4d5c57ea9a6940dd891ad53e9dbe8da0	0		7593	7298	
4	ae264e3637204a6fb9bb56bc8210ddfd	0		7658	6716	
5	9b98b8c7a33c4b65b9aebfe6a799e6d9	0		7677	4171	
6	2906b810c7d4411798c6938adc9daaa5	0		7632	4118	
7	5a8bc65990b245e5a138643cd4eb9837	0		7618	6687	
8	0b1e1539f2cc45b7b9fa7c272da2e1d7	0		7668	2663	
9	3f207df678b143eea3cee63160fa8bed	0		7617	4144	

	offer_completed
0	5317
1	5156
2	4296
3	3331
4	3688
5	4354
6	4017
7	0
8	3420
9	0

The above dataframe shows the response of various of customers towards the various offer\_ids

This shows that offer\_id with least completion are 5a8bc65990b245e5a138643cd4eb9837 and 3f207df678b143eea3cee63160fa8bed

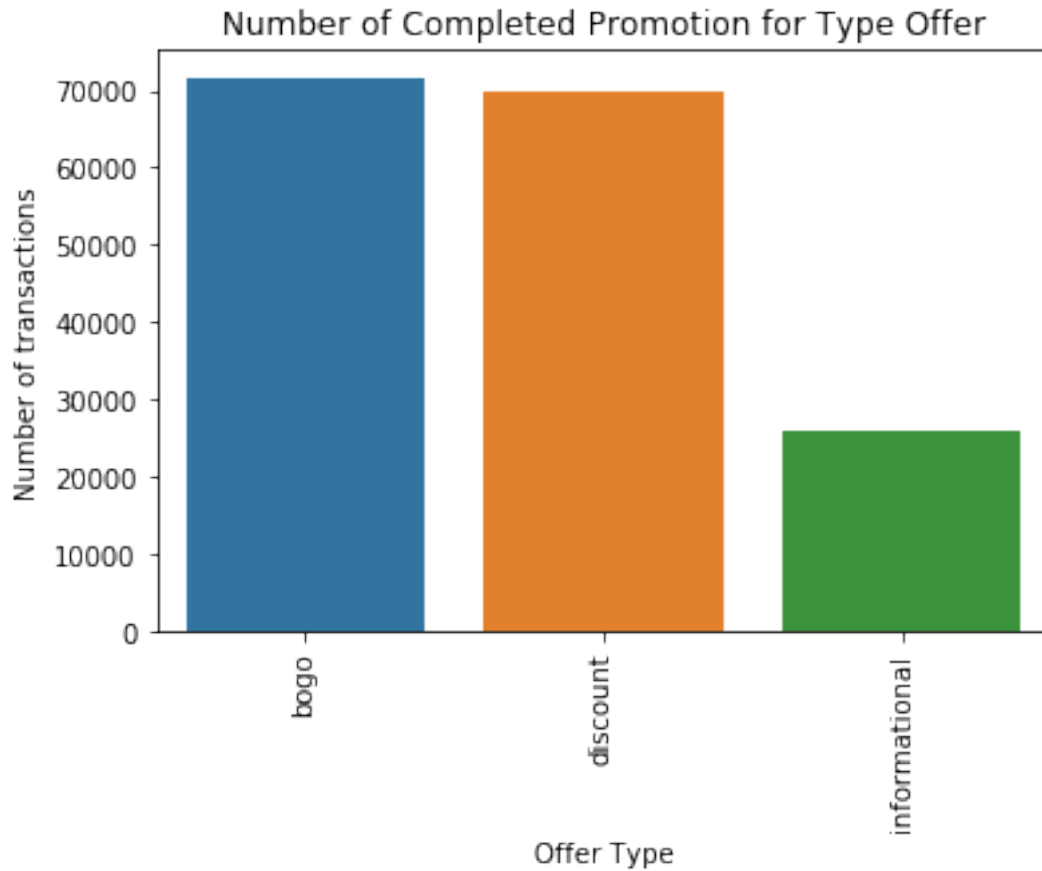
### Q7 Classification of offer\_ids into offer type

```
In [91]: def get_offer_type(offer_id):
    try:
        offer_type = portfolio[portfolio['id'] == offer_id]['offer_type'].values[0]
        return offer_type
    except:
        offer_type = 'NA'
        return offer_type

transcript['offer_type_map'] = transcript.apply(lambda x: get_offer_type(x['offer_id']))

In [92]: sns.countplot(transcript[transcript['offer_type_map'] != 'NA']['offer_type_map'])
plt.title('Number of Completed Promotion for Type Offer')
plt.ylabel('Number of transactions')
plt.xlabel('Offer Type')
```

```
plt.xticks(rotation = 90)
plt.show();
```



We can see that bogo and discount offers are offeres in a lot compared to informational offers

In [93]: transcript

```
Out [93]:
```

	event	person	time	\
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	0	
1	offer received	a03223e636434f42ac4c3df47e8bac43	0	
2	offer received	e2127556f4f64592b11af22de27a7932	0	
3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	0	
4	offer received	68617ca6246f4fbc85e91a2a49552598	0	
5	offer received	389bc3fa690240e798340f5a15918d5c	0	
6	offer received	c4863c7985cf408faee930f111475da3	0	
7	offer received	2eeac8d8feae4a8cad5a6af0499a211d	0	
8	offer received	aa4862eba776480b8bb9c68455b8c2e1	0	
9	offer received	31dda685af34476cad5bc968bdb01c53	0	
10	offer received	744d603ef08c4f33af5a61c8c7628d1c	0	
11	offer received	3d02345581554e81b7b289ab5e288078	0	
12	offer received	4b0da7e80e5945209a1fdddf813dbe0	0	

13	offer received	c27e0d6ab72c455a8bb66d980963de60	0
14	offer received	d53717f5400c4e84affdaeda9dd926b3	0
15	offer received	f806632c011441378d4646567f357a21	0
16	offer received	d058f73bf8674a26a95227db098147b1	0
17	offer received	65aba5c617294649aeb624da249e1ee5	0
18	offer received	ebe7ef46ea6f4963a7dd49f501b26779	0
19	offer received	1e9420836d554513ab90eba98552d0a9	0
20	offer received	868317b9be554cb18e50bc68484749a2	0
21	offer received	f082d80f0aac47a99173ba8ef8fc1909	0
22	offer received	102e9454054946fda62242d2e176fdce	0
23	offer received	4beeb3ed64dd4898b0edf2f6b67426d3	0
24	offer received	9f30b375d7bd4c62a884ffe7034e09ee	0
25	offer received	25c906289d154b66bf579693f89481c9	0
26	offer received	6e014185620b49bd98749f728747572f	0
27	offer received	02c083884c7d45b39cc68e1314fec56c	0
28	offer received	c0d210398dee4a0895b24444a5fcd1d2	0
29	offer received	8be4463721e14d7fa600686bf8c8b2ed	0
...	...	...	...
306504	transaction	8524d450673b4c24869b6c94380006de	714
306505	transaction	b895c57e8cd047a8872ce02aa54759d6	714
306506	offer completed	b895c57e8cd047a8872ce02aa54759d6	714
306507	offer viewed	8dda575c2a1d44b9ac8e8b07b93d1f8e	714
306508	transaction	8431c16f8e1d440880db371a68f82dd0	714
306509	offer completed	8431c16f8e1d440880db371a68f82dd0	714
306510	transaction	ba620885e51c4b0ea64a4f61daad494f	714
306511	transaction	a1a8f40407c444cc848468275308958a	714
306512	transaction	8d80970192fa496f99d6b45c470a4b60	714
306513	transaction	bde275066f3c4fa0bff3093e3b866a2c	714
306514	transaction	f1e4fd36e5a0446f83861308bddf6945	714
306515	transaction	0b64be3b241c4407a5c9a71781173829	714
306516	transaction	86d03d35d7e0434b935e7743e83be3a0	714
306517	transaction	3408fd05c781401f8442fb6dbaaea9c7	714
306518	transaction	1593d617fac246ef8e50dbb0ffd77f5f	714
306519	transaction	f1b31d07b5d84f69a2d5f1d07843989e	714
306520	transaction	2ce987015ec0404a97ba333e8e814090	714
306521	transaction	2e33545f0a764d27b2ccff95fc8d72c4	714
306522	transaction	d1c4500ace2e45e9a45d3cd2fccac8d8	714
306523	transaction	b65affd9e07346a1906364a396950e3d	714
306524	transaction	d613ca9c59dd42f497bdbf6178da54a7	714
306525	transaction	eec70ab28af74a22a4aeb889c0317944	714
306526	transaction	24f56b5e1849462093931b164eb803b5	714
306527	offer completed	24f56b5e1849462093931b164eb803b5	714
306528	transaction	5ca2620962114246ab218fc648eb3934	714
306529	transaction	b3a1272bc9904337b331bf348c3e8c17	714
306530	transaction	68213b08d99a4ae1b0dcb72aebd9aa35	714
306531	transaction	a00058cf10334a308c68e7631c529907	714
306532	transaction	76ddbd6576844afe811f1a3c0fbb5bec	714
306533	transaction	c02b10e8752c4d8e9b73f918558531f7	714

	value \
0	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}
1	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
2	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}
3	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}
4	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}
5	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}
6	{'offer id': '2298d6c36e964ae4a3e7e9706d1fb8c2'}
7	{'offer id': '3f207df678b143eea3cee63160fa8bed'}
8	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
9	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
10	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
11	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
12	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}
13	{'offer id': '3f207df678b143eea3cee63160fa8bed'}
14	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
15	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}
16	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
17	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}
18	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}
19	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}
20	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}
21	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}
22	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}
23	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}
24	{'offer id': '2298d6c36e964ae4a3e7e9706d1fb8c2'}
25	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}
26	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}
27	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}
28	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}
29	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}
...	...
306504	{'amount': 4.89}
306505	{'amount': 4.48}
306506	{'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...
306507	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
306508	{'amount': 1.19}
306509	{'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...
306510	{'amount': 14.31}
306511	{'amount': 2.37}
306512	{'amount': 6.92}
306513	{'amount': 12.73}
306514	{'amount': 8.2}
306515	{'amount': 2.6}
306516	{'amount': 9.2}
306517	{'amount': 11.7}
306518	{'amount': 40.67}

```

306519                                {'amount': 31.13}
306520                                {'amount': 1.6400000000000001}
306521                                {'amount': 17.35}
306522                                {'amount': 4.42}
306523                                {'amount': 18.35}
306524                                {'amount': 25.14}
306525                                {'amount': 43.58}
306526                                {'amount': 22.64}
306527 {'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...
306528                                {'amount': 2.2}
306529                                {'amount': 1.5899999999999999}
306530                                {'amount': 9.53}
306531                                {'amount': 3.61}
306532                                {'amount': 3.5300000000000002}
306533                                {'amount': 4.05}

```

	offer_id	reward	amount	offer_type_map
0	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0	bogo
1	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
2	2906b810c7d4411798c6938adc9daaa5	0	0	discount
3	fafdcd668e3743c1bb461111dcafc2a4	0	0	discount
4	4d5c57ea9a6940dd891ad53e9dbe8da0	0	0	bogo
5	f19421c1d4aa40978ebb69ca19b0e20d	0	0	bogo
6	2298d6c36e964ae4a3e7e9706d1fb8c2	0	0	discount
7	3f207df678b143eea3cee63160fa8bed	0	0	informational
8	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
9	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
10	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
11	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
12	ae264e3637204a6fb9bb56bc8210ddfd	0	0	bogo
13	3f207df678b143eea3cee63160fa8bed	0	0	informational
14	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
15	fafdcd668e3743c1bb461111dcafc2a4	0	0	discount
16	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
17	2906b810c7d4411798c6938adc9daaa5	0	0	discount
18	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0	bogo
19	ae264e3637204a6fb9bb56bc8210ddfd	0	0	bogo
20	2906b810c7d4411798c6938adc9daaa5	0	0	discount
21	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0	bogo
22	4d5c57ea9a6940dd891ad53e9dbe8da0	0	0	bogo
23	2906b810c7d4411798c6938adc9daaa5	0	0	discount
24	2298d6c36e964ae4a3e7e9706d1fb8c2	0	0	discount
25	2906b810c7d4411798c6938adc9daaa5	0	0	discount
26	f19421c1d4aa40978ebb69ca19b0e20d	0	0	bogo
27	ae264e3637204a6fb9bb56bc8210ddfd	0	0	bogo
28	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0	bogo
29	fafdcd668e3743c1bb461111dcafc2a4	0	0	discount
...	...	...	...	...



306504		0	4	NA
306505		0	4	NA
306506	fafdc668e3743c1bb461111dcafc2a4	2	0	discount
306507	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
306508		0	1	NA
306509	fafdc668e3743c1bb461111dcafc2a4	2	0	discount
306510		0	14	NA
306511		0	2	NA
306512		0	6	NA
306513		0	12	NA
306514		0	8	NA
306515		0	2	NA
306516		0	9	NA
306517		0	11	NA
306518		0	40	NA
306519		0	31	NA
306520		0	1	NA
306521		0	17	NA
306522		0	4	NA
306523		0	18	NA
306524		0	25	NA
306525		0	43	NA
306526		0	22	NA
306527	fafdc668e3743c1bb461111dcafc2a4	2	0	discount
306528		0	2	NA
306529		0	1	NA
306530		0	9	NA
306531		0	3	NA
306532		0	3	NA
306533		0	4	NA

[306534 rows x 8 columns]

```
In [94]: transcript['person'][transcript['event']=='offer completed'].value_counts()
```

```
Out[94]: e22206bf65234c0e9f273bef859c02a1    6
a20c4cf47deb418f8e995c9015f15fda    6
8c410d84af08408fb41f953c93ffac27    6
9c569de8e9f747bcb5c8f78c0a014fc5    6
516e91869c8546d8a885401e850ce66c    6
f1d65ae63f174b8f80fa063adcaa63b7    6
cc328665db7d4f77babe3cb7c87e2e2f    6
c94c15ddd30845faaf072d20b111aa1e    6
94ce14b4e3774ecd908575ba7ab32f85    6
f31e27cdcdac4b0a9a384c0567a7ae43    6
9196c2bfb739494f902a13bab46199d2    6
1e5d6388b5214fefb090a9a2a4d21983    6
41eb66dfb4824a029f7abb81c140c267    6
```

7055b5fa5f8647618aa14e220b7c6b5c	6
07e29d02d0074da28b430e1dc40cc1fc	6
06d7f5abc31b4a02836349333ac02f33	6
aa445cee24ba41389eadabcf2fc95bac	6
d80f9e3f974448ec902c42818097ebf3	6
0494aa6671414fab9837fa3cd45e72bc	6
759c2269abc44dfdb8e6d140d4060856	6
adc7ef85f1714699b4f341a7e12c632f	6
a0db7a1fb55e402cb7f5b8ddc10b0818	6
82980813d7094cf5878dd906a6734307	6
bdfba75f0e0c4533b4b6b97fa37daa4f	6
325da16cf16c4d72972f28281f752201	6
acdf9a19b60d4c13ad594ebcb6b23eb9	6
cb45be0c399a4b4fa13dda5c89c442f4	6
4357cb4e15f04f988045c5a7e37c5775	6
76018bc0dfd64ccc8f2e7959bf627ba7	6
5c2a03a9d03145cc9bf953faa2c51fc1	6
..	
9c692f9c82634eae9b881367b008c242	1
f7977eccb81b49b9ac6d2bd84cd64bb0	1
ee6d71acc74a4b1183ef4a2822e652e5	1
99b18b650c2745489bf81a306852a7c5	1
0e18338db3524564870a52ee5cfe68a4	1
332aa1f51a7643199d9d60f885230511	1
3b65578368194a428d38390dd27cd447	1
32fedc747de04e508c6a538f78b130f0	1
62dd66d3bb1c4153b6126caa0a9f8235	1
c06029a8eea747d69a13b52d58f4ccbb	1
cca43d4a61554c78abb7b62c3dc9927c	1
af046d91eec74ac79e40b6c12004ecab	1
61e81e0f321d49e7a62c44a2595c3bab	1
65daaf0f413744789903a355d6370b9d	1
5139d8d43e674e5d9dcd6773d9684462	1
e6590c7f954f4ff482c069b45070b351	1
7bf785bb8b6c4a5bb14815ca85ceb87b	1
85a4b98da3254e0986fc5a1ee9d5c1cc	1
3ecd6653a2d145a4b2bc3b35e8aece7a	1
a305233f5c944df5bcaacc029658e085	1
2814e3e30f2749a1bab4c14ee51de542	1
8aa2f57d85934578b6a5da5682500d08	1
fd64a3758d0b49549df03a5c25ba89c9	1
7651ccd65fa7484d972f75f2f2307010	1
bcfc432fc0be4938a9a688c5c2873a49	1
1dbb8d4481aa4b0c8c9b8912fb340c76	1
edfe76e1510841d79f0ecd0472e4680d	1
e6d3335fdf2c4cd2ac8edcd2bb06b289	1
58ad7189fe54463fa221873e553f3173	1
b1a6c6b97e114a75adbd008e9222397e	1

Name: person, Length: 12774, dtype: int64

```
In [95]: heavy_buying_customer =transcript[(transcript['event']=='offer_completed') | (transcrip
```

```
In [96]: unique_customer=transcript[(transcript['event']=='offer_completed') | (transcript['even
```

```
In [97]: customer_df=pd.DataFrame(unique_customer)
```

```
In [98]: amount=pd.DataFrame(columns=['amount'])
```

```
In [99]: customer_df=customer_df.join([amount])
customer_df
```

```
Out [99]:
```

		0 amount
0	02c083884c7d45b39cc68e1314fec56c	NaN
1	9fa9ae8f57894cc9a3b8a9bbe0fc1b2f	NaN
2	54890f68699049c2a04d415abc25e717	NaN
3	b2f1cd155b864803ad8334cdf13c4bd2	NaN
4	fe97aa22dd3e48c8b143116a8403dd52	NaN
5	629fc02d56414d91bca360decdfa9288	NaN
6	bbeb54e861614fc7b22a8844f72dca6c	NaN
7	a97e6f33219c432db82acfa0d19c602d	NaN
8	676506bad68e4161b9bbaffeb039626b	NaN
9	8f7dd3b2afe14c078eb4f6e6fe4ba97d	NaN
10	4cbe33c601a5407f8202086565c55111	NaN
11	b432b74402bb4981a4651c8df1670365	NaN
12	a04fcfd571034456aaa6d56c0a3fd9b6	NaN
13	227f2d69e46a4899b70d48182822cff6	NaN
14	bb0f25e23a4c4de6a645527c275cd594	NaN
15	c2c72ce6038644c797208046d1e3498a	NaN
16	7ca349e55ff544c7a13addfdea2e2c06	NaN
17	d72d201be5794279aa716d8ad82b8d90	NaN
18	ad80753fc9e0485c9e6b1cc9478d827f	NaN
19	73ffefd41e9a4ca3ab26b2b3697c6eb7	NaN
20	3e621194f72e40d7a0b695ee9b7c38b7	NaN
21	1f5c961416e64c5d88098b02b1bdf246	NaN
22	3bcc51fdde354eb1949c813dbc905182	NaN
23	ed46fca6de7042478b411690878dc069	NaN
24	b860d355ef6e4c66b5d5a837c56ef32d	NaN
25	4ad3748475204cf99571183f05b5e2f7	NaN
26	99297ea01107436fa8c2e2bc86f55d89	NaN
27	24115a61df25473e84a8a03f3c98de1a	NaN
28	7195944f0cc34115b0a5e7b4a62055f2	NaN
29	afce4cf8194f4e90a3e92da941a23601	NaN
...	...	...
16548	99ffa82129904cd6adabcdfe02072904	NaN
16549	d448fa911f3f4b4aafe87396d220fad6	NaN
16550	cfefa4c2c2aa40a196f392e43eb5eed	NaN
16551	6b214a99748949608e302160c8845f7f	NaN

16552	47e28072fc414f54bf1aa27be3a19d32	NaN
16553	25015650d5fb4a8b96e6d289e76cc892	NaN
16554	54d60cf626294a1685867c5f31dbf7b8	NaN
16555	3be15bacb2064198874cbf898ca5cf82	NaN
16556	2dbb5a86750d4f589ef19c4bf0dd1b3a	NaN
16557	8578196a074a4f328976e334fa9383a3	NaN
16558	4d3e33d680e04a57a565c847948bf1ca	NaN
16559	db1805ed333844978e8b46ed3e4643ae	NaN
16560	5ebe9f31969a453da31dd70fedd6c1eb	NaN
16561	39145fee7c1240469a46bf939fb8370c	NaN
16562	2ad98e767e5c472cbdf9e44a87366ef7	NaN
16563	2a6bb506b41540378b1d373985502233	NaN
16564	00ee2ca6421c4af0aeca60a1b3e00f6c	NaN
16565	695d4738abe7406da6966df59a1cd4fc	NaN
16566	77961f4298bd4340a3988bde6754d19d	NaN
16567	dc9d14e5d3be406b99e0d7e9a859bec0	NaN
16568	f6581b347e914638a6e04e3a5285a31d	NaN
16569	fef4f14201c44ddd915f504b7d88bf08	NaN
16570	fe285265878948309a32b47b216d2a65	NaN
16571	aabc3d56a2ea4446bef4c3f9eec8ab72	NaN
16572	999338157fd54f639b089cef0038e06a	NaN
16573	542c41f5afc049e7ae7d4721ace9d286	NaN
16574	448dabde725040978b8a247a20bac126	NaN
16575	7718656997f3453db0f5aeca9cd35240	NaN
16576	54463e5d95124b7fb3133fc1eae71952	NaN
16577	0c027f5f34dd4b9eba0a25785c611273	NaN

[16578 rows x 2 columns]

Q8 For all the unique customers how much amount do they spend and who all are the loyal customers

```
In [100]: op=0 # for all unique customers the amount they spend for various offers is added
          for customer in heavy_buying_customer:
              customer_df.amount[op]=customer[1]['amount'].sum()
              op=op+1
```

```
In [101]: customer_df=customer_df.sort_values(['amount'],ascending=False)
```

```
In [102]: customer_df.head(10)
```

```
Out[102]:
```

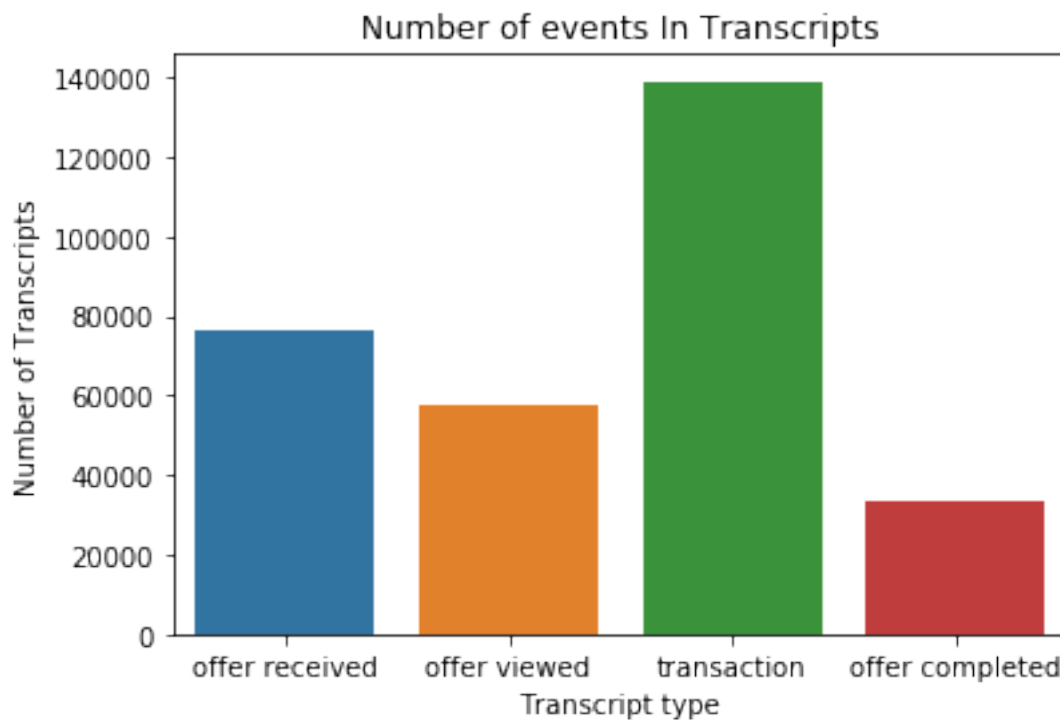
		0	amount
3929	e2f8376c32084327b1991706b124c8ed	1606	
15693	ed127151cf1c4c70bcb2c9a50ce749c8	1360	
11422	431a9ec074b44e80886ba3dfed6dfe2f	1320	
7492	8571868385524806bcacd7e73c1ae5e1	1314	
6366	6118ca1b782a4df0a852406b194219b2	1314	
5358	408574b846484c9f97f458b678a01a0e	1285	
11334	9407a3a0c9114b15b05f7704d0b40ef0	1256	

13672	c2df0a0925684591975861d7622ac296	1244
9673	7784652beb5d4a26955c561b63f3099b	1224
6484	ae5f3528d8324fcbdbbc51cf8a46cffa	1206

These are the top spenders

Q9 distribution of events in transcript

```
In [103]: sns.countplot(transcript['event'])
plt.title('Number of events In Transcripts')
plt.ylabel('Number of Transcripts')
plt.xlabel('Transcript type')
plt.xticks(rotation = 0)
plt.show();
```



In [ ]:

Q10 What is the most common promotion among various age groups?

```
In [104]: #the person id from profile dataset is mapped to transcript dataset
def age_offer(id):
    age_group = profile[profile['id']==id]['age_by_decade'].values[0]
    return age_group
```

```
In [105]: transcript['age_offer']=transcript.apply(lambda x:age_offer(x['person']),axis=1)
```

```
In [106]: transcript.head()
```

```
Out[106]:
```

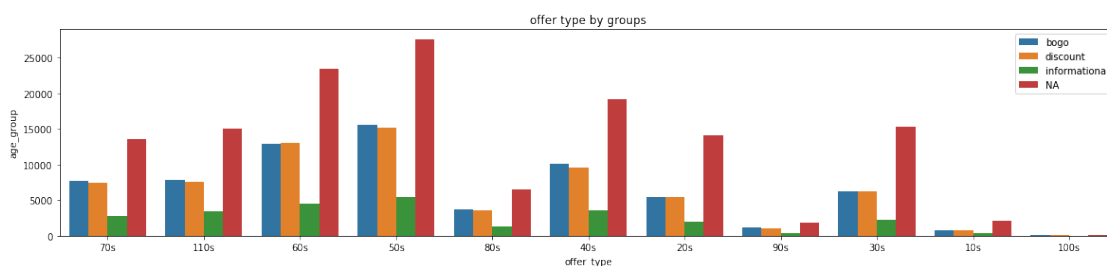
	event	person	time	value
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	0	
1	offer received	a03223e636434f42ac4c3df47e8bac43	0	
2	offer received	e2127556f4f64592b11af22de27a7932	0	
3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	0	
4	offer received	68617ca6246f4fbc85e91a2a49552598	0	

	offer_id	reward	amount	offer_type_map	age_offer
0	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0	bogo	70s
1	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount	110s
2	2906b810c7d4411798c6938adc9daaa5	0	0	discount	60s
3	fafdc668e3743c1bb461111dcafc2a4	0	0	discount	110s
4	4d5c57ea9a6940dd891ad53e9dbe8da0	0	0	bogo	110s

```
In [107]: plt.figure(figsize=(20,4))
sns.countplot(x="age_offer",hue="offer_type_map",data=transcript)
plt.xlabel("offer_type")
plt.ylabel("age_group")
plt.title("offer type by groups")
plt.legend()
```

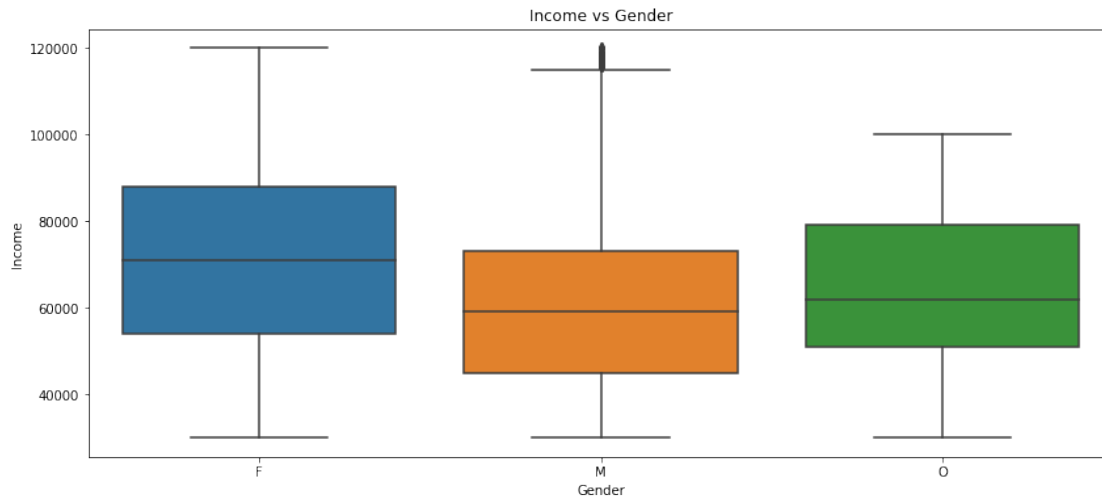
```
Out[107]: <matplotlib.legend.Legend at 0x7fc8c3f1d208>
```



The graph describes the distribution of offers among various age groups and also the unavailability of data in this respect

```
In [108]: plt.figure(figsize=(14, 6))
sns.boxplot(x=profile[profile['gender'] != 'NA']['gender'], y=profile['income'])
plt.title('Income vs Gender')
```

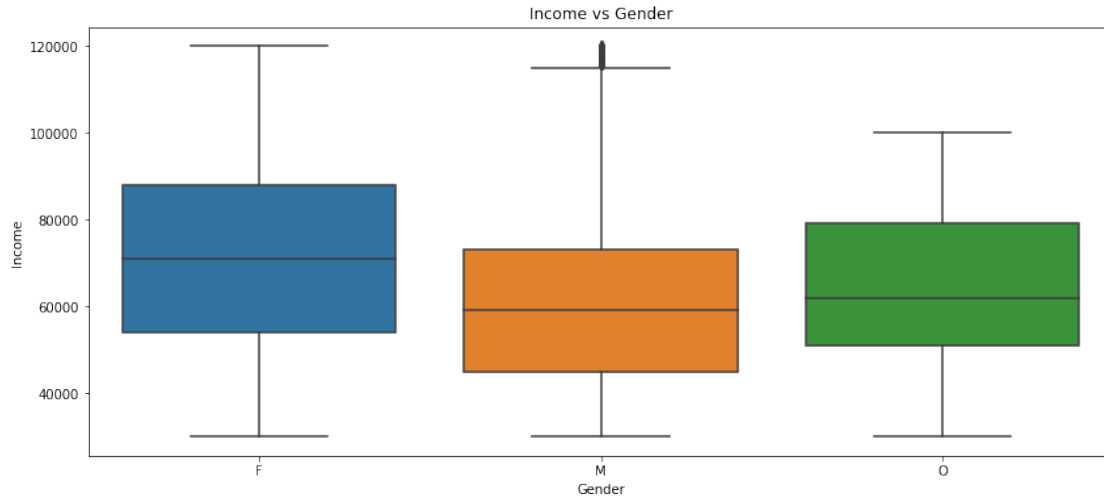
```
plt.ylabel('Income')
plt.xlabel('Gender')
plt.xticks(rotation = 0)
plt.show();
```



The above graph represents the income distribution among genders

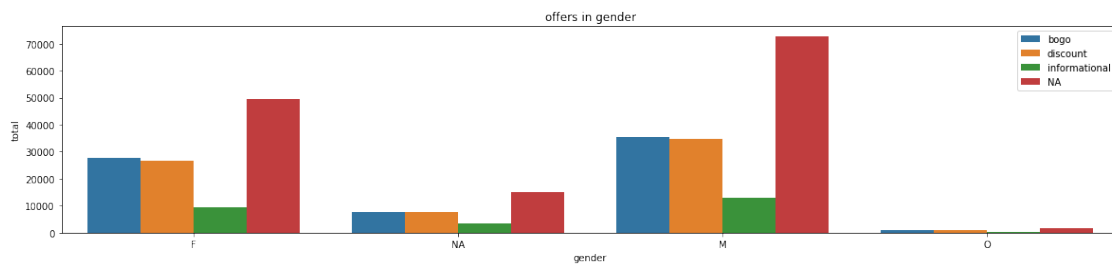
```
In [109]: def gender_offer(id):
            gender_of=profile[profile['id']==id]['gender'].values[0]
            return gender_of
            transcript['map_gender_offer']=transcript.apply(lambda x:gender_offer(x['person']),axis=1)

In [110]: plt.figure(figsize=(14, 6))
            sns.boxplot(x=profile[profile['gender'] != 'NA']['gender'], y=profile['income'])
            plt.title('Income vs Gender')
            plt.ylabel('Income')
            plt.xlabel('Gender')
            plt.xticks(rotation = 0)
            plt.show();
```



```
In [111]: plt.figure(figsize=(20,4))
sns.countplot(x="map_gender_offer",hue="offer_type_map",data=transcript)
plt.xlabel("gender")
plt.ylabel("total")
plt.title("offers in gender")
plt.legend()
```

Out[111]: <matplotlib.legend.Legend at 0x7fc8c3e49a90>

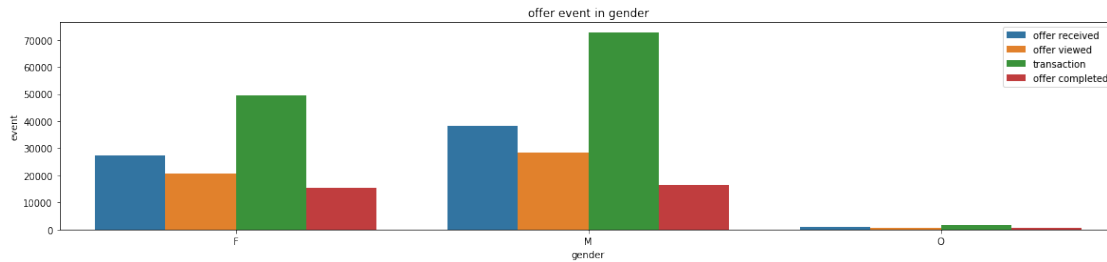


The graph shows the distribution of offers among genders

```
In [112]: plt.figure(figsize=(20,4))
sns.countplot(x=transcript[transcript["map_gender_offer"]!='NA']["map_gender_offer"],h
plt.xlabel("gender")
plt.ylabel("event")
plt.title("offer event in gender")
plt.legend()
```

Out[112]: <matplotlib.legend.Legend at 0x7fc8c3d8cc88>





```
In [113]: transcript.columns
```

```
Out[113]: Index(['event', 'person', 'time', 'value', 'offer_id', 'reward', 'amount',
                  'offer_type_map', 'age_offer', 'map_gender_offer'],
                  dtype='object')
```

From the above two graphs it is conclusive that males received more offers compared to woman and hence offer completion is also more for them

```
In [114]: offer_gender_type = transcript[transcript["map_gender_offer"] != 'NA'].groupby(['map_g
offer_gender_event = transcript[transcript["map_gender_offer"] != 'NA'].groupby(['map_g
```

```
In [115]: offer_gender_type,offer_gender_event
```

```
Out[115]: (
      map_gender_offer offer_type_map  event  person  time  value  offer_id  \
F      NA              49382    49382  49382  49382    49382
      bogo              27619    27619  27619  27619    27619
      discount          26652    26652  26652  26652    26652
      informational      9448     9448   9448   9448     9448
M      NA              72794    72794  72794  72794    72794
      bogo              35301    35301  35301  35301    35301
      discount          34739    34739  34739  34739    34739
      informational     12856    12856  12856  12856    12856
O      NA              1781     1781   1781   1781     1781
      bogo              914      914    914    914      914
      discount          920      920    920    920      920
      informational      356     356    356    356      356

      reward  amount  age_offer
map_gender_offer offer_type_map
F      NA      49382    49382    49382
      bogo      27619    27619    27619
      discount  26652    26652    26652
      informational  9448     9448     9448
M      NA      72794    72794    72794
      bogo      35301    35301    35301
```

	discount	34739	34739	34739		
	informational	12856	12856	12856		
0	NA	1781	1781	1781		
	bogo	914	914	914		
	discount	920	920	920		
	informational	356	356	356	,	
		person	time	value	offer_id	reward \
map_gender_offer	event					
F	offer completed	15477	15477	15477	15477	15477
	offer received	27456	27456	27456	27456	27456
	offer viewed	20786	20786	20786	20786	20786
	transaction	49382	49382	49382	49382	49382
M	offer completed	16466	16466	16466	16466	16466
	offer received	38129	38129	38129	38129	38129
	offer viewed	28301	28301	28301	28301	28301
	transaction	72794	72794	72794	72794	72794
0	offer completed	501	501	501	501	501
	offer received	916	916	916	916	916
	offer viewed	773	773	773	773	773
	transaction	1781	1781	1781	1781	1781
		amount	offer_type_map	age_offer		
map_gender_offer	event					
F	offer completed	15477		15477		15477
	offer received	27456		27456		27456
	offer viewed	20786		20786		20786
	transaction	49382		49382		49382
M	offer completed	16466		16466		16466
	offer received	38129		38129		38129
	offer viewed	28301		28301		28301
	transaction	72794		72794		72794
0	offer completed	501		501		501
	offer received	916		916		916
	offer viewed	773		773		773
	transaction	1781		1781		1781 )

**Q11 how are the people among various genders taking these offers and how effective the offers are?** the no of females completing the offer

```
In [116]: transcript[(transcript["map_gender_offer"]=="F") & (transcript["event"]=="offer comple
```

```
Out[116]: 15477
```

the no of males completing the offer

```
In [117]: transcript[(transcript["map_gender_offer"]=="M") & (transcript["event"]=="offer comple
```

```
Out[117]: 16466
```

the no of females receiving the offer

```
In [118]: transcript[(transcript["map_gender_offer"]=="F") & (transcript["event"]=="offer receive
```

```
Out[118]: 27456
```

the no of males receiving the offer

```
In [119]: transcript[(transcript["map_gender_offer"]=="M") & (transcript["event"]=="offer receive
```

```
Out[119]: 38129
```

the no of females viewing the offer

```
In [120]: transcript[(transcript["map_gender_offer"]=="F") & (transcript["event"]=="offer viewed
```

```
Out[120]: 20786
```

the no of males viewing the offer

```
In [121]: transcript[(transcript["map_gender_offer"]=="M") & (transcript["event"]=="offer viewed
```

```
Out[121]: 28301
```

the no of females completing the transaction

```
In [122]: transcript[(transcript["map_gender_offer"]=="F") & (transcript["event"]=="transaction"
```

```
Out[122]: 49382
```

the no of males completing the transaction

```
In [123]: transcript[(transcript["map_gender_offer"]=="M") & (transcript["event"]=="transaction"
```

```
Out[123]: 72794
```

Hence no of females who completed the offer is 15477 and no of males who completed the offer is 16466 and total number of females receiving the offer is 27456 and that of males is 38129 WITH 20786 females viewing the offer and 28301 males viewing the offer. Hence in proportion 56.37 % woman completed the offer and 43.6% woman only viewed the offer and in males 43.18% completed the offer and 56.81% viewed the offer with no of males receiving the offer more than no. of females. For transaction no of females doing transaction is 49382 and that of males is 72794

So we come to a conclusion that females are more in number for completing offers and male for transaction

adding income column into transcript data

```
In [124]: #taking people_id from profile dataset and mapping it to transcript to get their income
def income_pro(id):
    inc=profile[profile['id']==id]['income'].values[0]
    return inc
transcript['income']=transcript.apply(lambda x:income_pro(x['person']),axis=1)
```

converting all the datasets into csv file and saving

```
In [125]: transcript.to_csv("new_transcript.csv")
          portfolio.to_csv("new_portfolio.csv")
          profile.to_csv("new_profile.csv")
```

checking if there are any null values in the columns

```
In [126]: transcript.isna().sum()
```

```
Out[126]: event          0
          person        0
          time          0
          value         0
          offer_id      0
          reward        0
          amount        0
          offer_type_map 0
          age_offer     0
          map_gender_offer 0
          income        0
          dtype: int64
```

```
In [127]: portfolio.isna().sum()
```

```
Out[127]: difficulty    0
          duration      0
          id            0
          offer_type     0
          reward        0
          bogo          0
          discount      0
          informational  0
          email         0
          mobile        0
          social        0
          web           0
          dtype: int64
```

**MODELLING** Let the variable to be predicted be event in transcript

Following cells involve removal of some information and convertinf of some columns into dummies

```
In [128]: transcript
```

```
Out[128]:
```

	event	person	time	\
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	0	
1	offer received	a03223e636434f42ac4c3df47e8bac43	0	
2	offer received	e2127556f4f64592b11af22de27a7932	0	

3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	0
4	offer received	68617ca6246f4fbc85e91a2a49552598	0
5	offer received	389bc3fa690240e798340f5a15918d5c	0
6	offer received	c4863c7985cf408faee930f111475da3	0
7	offer received	2eeac8d8feae4a8cad5a6af0499a211d	0
8	offer received	aa4862eba776480b8bb9c68455b8c2e1	0
9	offer received	31dda685af34476cad5bc968bdb01c53	0
10	offer received	744d603ef08c4f33af5a61c8c7628d1c	0
11	offer received	3d02345581554e81b7b289ab5e288078	0
12	offer received	4b0da7e80e5945209a1fdddfe813dbe0	0
13	offer received	c27e0d6ab72c455a8bb66d980963de60	0
14	offer received	d53717f5400c4e84affdaeda9dd926b3	0
15	offer received	f806632c011441378d4646567f357a21	0
16	offer received	d058f73bf8674a26a95227db098147b1	0
17	offer received	65aba5c617294649aeb624da249e1ee5	0
18	offer received	ebe7ef46ea6f4963a7dd49f501b26779	0
19	offer received	1e9420836d554513ab90eba98552d0a9	0
20	offer received	868317b9be554cb18e50bc68484749a2	0
21	offer received	f082d80f0aac47a99173ba8ef8fc1909	0
22	offer received	102e9454054946fda62242d2e176fdce	0
23	offer received	4beeb3ed64dd4898b0edf2f6b67426d3	0
24	offer received	9f30b375d7bd4c62a884ffe7034e09ee	0
25	offer received	25c906289d154b66bf579693f89481c9	0
26	offer received	6e014185620b49bd98749f728747572f	0
27	offer received	02c083884c7d45b39cc68e1314fec56c	0
28	offer received	c0d210398dee4a0895b24444a5fcd1d2	0
29	offer received	8be4463721e14d7fa600686bf8c8b2ed	0
...	...	...	...
306504	transaction	8524d450673b4c24869b6c94380006de	714
306505	transaction	b895c57e8cd047a8872ce02aa54759d6	714
306506	offer completed	b895c57e8cd047a8872ce02aa54759d6	714
306507	offer viewed	8dda575c2a1d44b9ac8e8b07b93d1f8e	714
306508	transaction	8431c16f8e1d440880db371a68f82dd0	714
306509	offer completed	8431c16f8e1d440880db371a68f82dd0	714
306510	transaction	ba620885e51c4b0ea64a4f61daad494f	714
306511	transaction	a1a8f40407c444cc848468275308958a	714
306512	transaction	8d80970192fa496f99d6b45c470a4b60	714
306513	transaction	bde275066f3c4fa0bff3093e3b866a2c	714
306514	transaction	f1e4fd36e5a0446f83861308bddf6945	714
306515	transaction	0b64be3b241c4407a5c9a71781173829	714
306516	transaction	86d03d35d7e0434b935e7743e83be3a0	714
306517	transaction	3408fd05c781401f8442fb6dbaaea9c7	714
306518	transaction	1593d617fac246ef8e50dbb0ffd77f5f	714
306519	transaction	f1b31d07b5d84f69a2d5f1d07843989e	714
306520	transaction	2ce987015ec0404a97ba333e8e814090	714
306521	transaction	2e33545f0a764d27b2ccff95fc8d72c4	714
306522	transaction	d1c4500ace2e45e9a45d3cd2fccac8d8	714
306523	transaction	b65affd9e07346a1906364a396950e3d	714

306524	transaction	d613ca9c59dd42f497bdf6178da54a7	714
306525	transaction	eec70ab28af74a22a4aeb889c0317944	714
306526	transaction	24f56b5e1849462093931b164eb803b5	714
306527	offer completed	24f56b5e1849462093931b164eb803b5	714
306528	transaction	5ca2620962114246ab218fc648eb3934	714
306529	transaction	b3a1272bc9904337b331bf348c3e8c17	714
306530	transaction	68213b08d99a4ae1b0dcb72aebd9aa35	714
306531	transaction	a00058cf10334a308c68e7631c529907	714
306532	transaction	76ddb6576844afe811f1a3c0fbb5bec	714
306533	transaction	c02b10e8752c4d8e9b73f918558531f7	714

		value \
0	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	
1	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
2	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	
3	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}	
4	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}	
5	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}	
6	{'offer id': '2298d6c36e964ae4a3e7e9706d1fb8c2'}	
7	{'offer id': '3f207df678b143eea3cee63160fa8bed'}	
8	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
9	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
10	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
11	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
12	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}	
13	{'offer id': '3f207df678b143eea3cee63160fa8bed'}	
14	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
15	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}	
16	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
17	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	
18	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	
19	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}	
20	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	
21	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	
22	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}	
23	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	
24	{'offer id': '2298d6c36e964ae4a3e7e9706d1fb8c2'}	
25	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}	
26	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}	
27	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}	
28	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	
29	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}	
...		...
306504		{'amount': 4.89}
306505		{'amount': 4.48}
306506	{'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...	
306507	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}	
306508		{'amount': 1.19}

```

306509 {'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...
306510 {'amount': 14.31}
306511 {'amount': 2.37}
306512 {'amount': 6.92}
306513 {'amount': 12.73}
306514 {'amount': 8.2}
306515 {'amount': 2.6}
306516 {'amount': 9.2}
306517 {'amount': 11.7}
306518 {'amount': 40.67}
306519 {'amount': 31.13}
306520 {'amount': 1.6400000000000001}
306521 {'amount': 17.35}
306522 {'amount': 4.42}
306523 {'amount': 18.35}
306524 {'amount': 25.14}
306525 {'amount': 43.58}
306526 {'amount': 22.64}
306527 {'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...
306528 {'amount': 2.2}
306529 {'amount': 1.5899999999999999}
306530 {'amount': 9.53}
306531 {'amount': 3.61}
306532 {'amount': 3.5300000000000002}
306533 {'amount': 4.05}

```

	offer_id	reward	amount	offer_type_map \
0	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0	bogo
1	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
2	2906b810c7d4411798c6938adc9daaa5	0	0	discount
3	fafdcd668e3743c1bb461111dcafc2a4	0	0	discount
4	4d5c57ea9a6940dd891ad53e9dbe8da0	0	0	bogo
5	f19421c1d4aa40978ebb69ca19b0e20d	0	0	bogo
6	2298d6c36e964ae4a3e7e9706d1fb8c2	0	0	discount
7	3f207df678b143eea3cee63160fa8bed	0	0	informational
8	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
9	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
10	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
11	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
12	ae264e3637204a6fb9bb56bc8210ddfd	0	0	bogo
13	3f207df678b143eea3cee63160fa8bed	0	0	informational
14	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
15	fafdcd668e3743c1bb461111dcafc2a4	0	0	discount
16	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
17	2906b810c7d4411798c6938adc9daaa5	0	0	discount
18	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0	bogo
19	ae264e3637204a6fb9bb56bc8210ddfd	0	0	bogo
20	2906b810c7d4411798c6938adc9daaa5	0	0	discount

21	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0	bogo
22	4d5c57ea9a6940dd891ad53e9dbe8da0	0	0	bogo
23	2906b810c7d4411798c6938adc9daaa5	0	0	discount
24	2298d6c36e964ae4a3e7e9706d1fb8c2	0	0	discount
25	2906b810c7d4411798c6938adc9daaa5	0	0	discount
26	f19421c1d4aa40978ebb69ca19b0e20d	0	0	bogo
27	ae264e3637204a6fb9bb56bc8210ddfd	0	0	bogo
28	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0	bogo
29	fafdc668e3743c1bb461111dcafc2a4	0	0	discount
...	...	...	...	...
306504		0	4	NA
306505		0	4	NA
306506	fafdc668e3743c1bb461111dcafc2a4	2	0	discount
306507	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
306508		0	1	NA
306509	fafdc668e3743c1bb461111dcafc2a4	2	0	discount
306510		0	14	NA
306511		0	2	NA
306512		0	6	NA
306513		0	12	NA
306514		0	8	NA
306515		0	2	NA
306516		0	9	NA
306517		0	11	NA
306518		0	40	NA
306519		0	31	NA
306520		0	1	NA
306521		0	17	NA
306522		0	4	NA
306523		0	18	NA
306524		0	25	NA
306525		0	43	NA
306526		0	22	NA
306527	fafdc668e3743c1bb461111dcafc2a4	2	0	discount
306528		0	2	NA
306529		0	1	NA
306530		0	9	NA
306531		0	3	NA
306532		0	3	NA
306533		0	4	NA

	age_offer	map_gender_offer	income
0	70s	F	100000.000000
1	110s	NA	65404.991568
2	60s	M	70000.000000
3	110s	NA	65404.991568
4	110s	NA	65404.991568
5	60s	M	53000.000000



6	110s	NA	65404.991568
7	50s	M	51000.000000
8	60s	F	57000.000000
9	60s	F	71000.000000
10	110s	NA	65404.991568
11	110s	NA	65404.991568
12	60s	M	100000.000000
13	70s	F	71000.000000
14	80s	F	53000.000000
15	40s	M	69000.000000
16	50s	F	88000.000000
17	110s	NA	65404.991568
18	50s	M	41000.000000
19	20s	M	70000.000000
20	90s	F	89000.000000
21	40s	M	33000.000000
22	60s	F	57000.000000
23	110s	NA	65404.991568
24	20s	F	63000.000000
25	110s	NA	65404.991568
26	70s	M	40000.000000
27	20s	F	30000.000000
28	40s	M	33000.000000
29	110s	NA	65404.991568
...	...	...	...
306504	70s	M	75000.000000
306505	110s	NA	65404.991568
306506	110s	NA	65404.991568
306507	60s	F	64000.000000
306508	30s	M	39000.000000
306509	30s	M	39000.000000
306510	30s	F	68000.000000
306511	60s	M	63000.000000
306512	30s	M	62000.000000
306513	30s	M	65000.000000
306514	40s	M	56000.000000
306515	60s	F	42000.000000
306516	50s	F	53000.000000
306517	20s	M	48000.000000
306518	100s	F	82000.000000
306519	60s	M	84000.000000
306520	30s	M	61000.000000
306521	40s	M	64000.000000
306522	80s	M	59000.000000
306523	40s	M	69000.000000
306524	40s	F	68000.000000
306525	50s	M	95000.000000
306526	40s	F	80000.000000

306527	40s	F	80000.000000
306528	110s	NA	65404.991568
306529	60s	M	47000.000000
306530	50s	M	62000.000000
306531	60s	F	52000.000000
306532	50s	M	40000.000000
306533	110s	NA	65404.991568

[306534 rows x 11 columns]

Removing all 'NA' in transcript.event

```
In [129]: tran=transcript[transcript['event']!='NA']
```

```
In [ ]:
```

converting event column into different columns as per the various events

```
In [130]: data=pd.get_dummies(transcript['event'])
```

```
In [131]: tran=tran.join(data) #joining data and tran
```

```
In [132]: tran=tran.drop('value',axis=1)
```

```
In [133]: data=pd.get_dummies(transcript['offer_type_map']) #dumming offer_type_map column
```

```
In [134]: tran=tran.join(data) #joining data and tran
```

```
In [135]: data=pd.get_dummies(transcript['offer_id']) #dumming offer_id column
```

```
In [136]: tran=tran.join(data) #joining data and tran
```

```
In [137]: tran
```

```
Out[137]:
```

	event	person	time	\
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	0	
1	offer received	a03223e636434f42ac4c3df47e8bac43	0	
2	offer received	e2127556f4f64592b11af22de27a7932	0	
3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	0	
4	offer received	68617ca6246f4fbc85e91a2a49552598	0	
5	offer received	389bc3fa690240e798340f5a15918d5c	0	
6	offer received	c4863c7985cf408faee930f111475da3	0	
7	offer received	2eeac8d8feae4a8cad5a6af0499a211d	0	
8	offer received	aa4862eba776480b8bb9c68455b8c2e1	0	
9	offer received	31dda685af34476cad5bc968bdb01c53	0	
10	offer received	744d603ef08c4f33af5a61c8c7628d1c	0	
11	offer received	3d02345581554e81b7b289ab5e288078	0	
12	offer received	4b0da7e80e5945209a1fdddfe813dbe0	0	
13	offer received	c27e0d6ab72c455a8bb66d980963de60	0	
14	offer received	d53717f5400c4e84affdaeda9dd926b3	0	

15	offer received	f806632c011441378d4646567f357a21	0
16	offer received	d058f73bf8674a26a95227db098147b1	0
17	offer received	65aba5c617294649aeb624da249e1ee5	0
18	offer received	ebe7ef46ea6f4963a7dd49f501b26779	0
19	offer received	1e9420836d554513ab90eba98552d0a9	0
20	offer received	868317b9be554cb18e50bc68484749a2	0
21	offer received	f082d80f0aac47a99173ba8ef8fc1909	0
22	offer received	102e9454054946fda62242d2e176fdce	0
23	offer received	4beeb3ed64dd4898b0edf2f6b67426d3	0
24	offer received	9f30b375d7bd4c62a884ffe7034e09ee	0
25	offer received	25c906289d154b66bf579693f89481c9	0
26	offer received	6e014185620b49bd98749f728747572f	0
27	offer received	02c083884c7d45b39cc68e1314fec56c	0
28	offer received	c0d210398dee4a0895b24444a5fcd1d2	0
29	offer received	8be4463721e14d7fa600686bf8c8b2ed	0
...	...	...	...
306504	transaction	8524d450673b4c24869b6c94380006de	714
306505	transaction	b895c57e8cd047a8872ce02aa54759d6	714
306506	offer completed	b895c57e8cd047a8872ce02aa54759d6	714
306507	offer viewed	8dda575c2a1d44b9ac8e8b07b93d1f8e	714
306508	transaction	8431c16f8e1d440880db371a68f82dd0	714
306509	offer completed	8431c16f8e1d440880db371a68f82dd0	714
306510	transaction	ba620885e51c4b0ea64a4f61daad494f	714
306511	transaction	a1a8f40407c444cc848468275308958a	714
306512	transaction	8d80970192fa496f99d6b45c470a4b60	714
306513	transaction	bde275066f3c4fa0bff3093e3b866a2c	714
306514	transaction	f1e4fd36e5a0446f83861308bddf6945	714
306515	transaction	0b64be3b241c4407a5c9a71781173829	714
306516	transaction	86d03d35d7e0434b935e7743e83be3a0	714
306517	transaction	3408fd05c781401f8442fb6dbaaea9c7	714
306518	transaction	1593d617fac246ef8e50dbb0ffd77f5f	714
306519	transaction	f1b31d07b5d84f69a2d5f1d07843989e	714
306520	transaction	2ce987015ec0404a97ba333e8e814090	714
306521	transaction	2e33545f0a764d27b2ccff95fc8d72c4	714
306522	transaction	d1c4500ace2e45e9a45d3cd2fccac8d8	714
306523	transaction	b65affd9e07346a1906364a396950e3d	714
306524	transaction	d613ca9c59dd42f497bdbf6178da54a7	714
306525	transaction	eec70ab28af74a22a4aeb889c0317944	714
306526	transaction	24f56b5e1849462093931b164eb803b5	714
306527	offer completed	24f56b5e1849462093931b164eb803b5	714
306528	transaction	5ca2620962114246ab218fc648eb3934	714
306529	transaction	b3a1272bc9904337b331bf348c3e8c17	714
306530	transaction	68213b08d99a4ae1b0dcb72aebd9aa35	714
306531	transaction	a00058cf10334a308c68e7631c529907	714
306532	transaction	76ddbd6576844afe811f1a3c0fbb5bec	714
306533	transaction	c02b10e8752c4d8e9b73f918558531f7	714

offer\_id reward amount offer\_type\_map \

0	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0	bogo
1	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
2	2906b810c7d4411798c6938adc9daaa5	0	0	discount
3	fafdc668e3743c1bb461111dcafc2a4	0	0	discount
4	4d5c57ea9a6940dd891ad53e9dbe8da0	0	0	bogo
5	f19421c1d4aa40978ebb69ca19b0e20d	0	0	bogo
6	2298d6c36e964ae4a3e7e9706d1fb8c2	0	0	discount
7	3f207df678b143eea3cee63160fa8bed	0	0	informational
8	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
9	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
10	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
11	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
12	ae264e3637204a6fb9bb56bc8210ddfd	0	0	bogo
13	3f207df678b143eea3cee63160fa8bed	0	0	informational
14	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
15	fafdc668e3743c1bb461111dcafc2a4	0	0	discount
16	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
17	2906b810c7d4411798c6938adc9daaa5	0	0	discount
18	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0	bogo
19	ae264e3637204a6fb9bb56bc8210ddfd	0	0	bogo
20	2906b810c7d4411798c6938adc9daaa5	0	0	discount
21	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0	bogo
22	4d5c57ea9a6940dd891ad53e9dbe8da0	0	0	bogo
23	2906b810c7d4411798c6938adc9daaa5	0	0	discount
24	2298d6c36e964ae4a3e7e9706d1fb8c2	0	0	discount
25	2906b810c7d4411798c6938adc9daaa5	0	0	discount
26	f19421c1d4aa40978ebb69ca19b0e20d	0	0	bogo
27	ae264e3637204a6fb9bb56bc8210ddfd	0	0	bogo
28	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0	bogo
29	fafdc668e3743c1bb461111dcafc2a4	0	0	discount
...	...	...	...	...
306504		0	4	NA
306505		0	4	NA
306506	fafdc668e3743c1bb461111dcafc2a4	2	0	discount
306507	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0	discount
306508		0	1	NA
306509	fafdc668e3743c1bb461111dcafc2a4	2	0	discount
306510		0	14	NA
306511		0	2	NA
306512		0	6	NA
306513		0	12	NA
306514		0	8	NA
306515		0	2	NA
306516		0	9	NA
306517		0	11	NA
306518		0	40	NA
306519		0	31	NA
306520		0	1	NA

306521		0	17	NA
306522		0	4	NA
306523		0	18	NA
306524		0	25	NA
306525		0	43	NA
306526		0	22	NA
306527	fafdc668e3743c1bb461111dcafc2a4	2	0	discount
306528		0	2	NA
306529		0	1	NA
306530		0	9	NA
306531		0	3	NA
306532		0	3	NA
306533		0	4	NA

	age_offer	map_gender_offer	income \
0	70s	F	100000.000000
1	110s	NA	65404.991568
2	60s	M	70000.000000
3	110s	NA	65404.991568
4	110s	NA	65404.991568
5	60s	M	53000.000000
6	110s	NA	65404.991568
7	50s	M	51000.000000
8	60s	F	57000.000000
9	60s	F	71000.000000
10	110s	NA	65404.991568
11	110s	NA	65404.991568
12	60s	M	100000.000000
13	70s	F	71000.000000
14	80s	F	53000.000000
15	40s	M	69000.000000
16	50s	F	88000.000000
17	110s	NA	65404.991568
18	50s	M	41000.000000
19	20s	M	70000.000000
20	90s	F	89000.000000
21	40s	M	33000.000000
22	60s	F	57000.000000
23	110s	NA	65404.991568
24	20s	F	63000.000000
25	110s	NA	65404.991568
26	70s	M	40000.000000
27	20s	F	30000.000000
28	40s	M	33000.000000
29	110s	NA	65404.991568
...	...	...	...
306504	70s	M	75000.000000
306505	110s	NA	65404.991568

306506	110s	NA	65404.991568
306507	60s	F	64000.000000
306508	30s	M	39000.000000
306509	30s	M	39000.000000
306510	30s	F	68000.000000
306511	60s	M	63000.000000
306512	30s	M	62000.000000
306513	30s	M	65000.000000
306514	40s	M	56000.000000
306515	60s	F	42000.000000
306516	50s	F	53000.000000
306517	20s	M	48000.000000
306518	100s	F	82000.000000
306519	60s	M	84000.000000
306520	30s	M	61000.000000
306521	40s	M	64000.000000
306522	80s	M	59000.000000
306523	40s	M	69000.000000
306524	40s	F	68000.000000
306525	50s	M	95000.000000
306526	40s	F	80000.000000
306527	40s	F	80000.000000
306528	110s	NA	65404.991568
306529	60s	M	47000.000000
306530	50s	M	62000.000000
306531	60s	F	52000.000000
306532	50s	M	40000.000000
306533	110s	NA	65404.991568

	...	0b1e1539f2cc45b7b9fa7c272da2e1d7 \
0	...	0
1	...	1
2	...	0
3	...	0
4	...	0
5	...	0
6	...	0
7	...	0
8	...	1
9	...	1
10	...	1
11	...	1
12	...	0
13	...	0
14	...	1
15	...	0
16	...	1
17	...	0

18	...	0
19	...	0
20	...	0
21	...	0
22	...	0
23	...	0
24	...	0
25	...	0
26	...	0
27	...	0
28	...	0
29	...	0
...	...	...
306504	...	0
306505	...	0
306506	...	0
306507	...	1
306508	...	0
306509	...	0
306510	...	0
306511	...	0
306512	...	0
306513	...	0
306514	...	0
306515	...	0
306516	...	0
306517	...	0
306518	...	0
306519	...	0
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306521	...	0
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306523	...	0
306524	...	0
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306526	...	0
306527	...	0
306528	...	0
306529	...	0
306530	...	0
306531	...	0
306532	...	0
306533	...	0
2298d6c36e964ae4a3e7e9706d1fb8c2 2906b810c7d4411798c6938adc9daaa5 \		
0	0	0
1	0	0
2	0	1

3	0	0
4	0	0
5	0	0
6	1	0
7	0	0
8	0	0
9	0	0
10	0	0
11	0	0
12	0	0
13	0	0
14	0	0
15	0	0
16	0	0
17	0	1
18	0	0
19	0	0
20	0	1
21	0	0
22	0	0
23	0	1
24	1	0
25	0	1
26	0	0
27	0	0
28	0	0
29	0	0
...	...	...
306504	0	0
306505	0	0
306506	0	0
306507	0	0
306508	0	0
306509	0	0
306510	0	0
306511	0	0
306512	0	0
306513	0	0
306514	0	0
306515	0	0
306516	0	0
306517	0	0
306518	0	0
306519	0	0
306520	0	0
306521	0	0
306522	0	0
306523	0	0



306524	0	0
306525	0	0
306526	0	0
306527	0	0
306528	0	0
306529	0	0
306530	0	0
306531	0	0
306532	0	0
306533	0	0
	3f207df678b143eea3cee63160fa8bed	4d5c57ea9a6940dd891ad53e9dbe8da0 \
0	0	0
1	0	0
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5	0	0
6	0	0
7	1	0
8	0	0
9	0	0
10	0	0
11	0	0
12	0	0
13	1	0
14	0	0
15	0	0
16	0	0
17	0	0
18	0	0
19	0	0
20	0	0
21	0	0
22	0	1
23	0	0
24	0	0
25	0	0
26	0	0
27	0	0
28	0	0
29	0	0
...	...	...
306504	0	0
306505	0	0
306506	0	0
306507	0	0
306508	0	0

306509	0	0
306510	0	0
306511	0	0
306512	0	0
306513	0	0
306514	0	0
306515	0	0
306516	0	0
306517	0	0
306518	0	0
306519	0	0
306520	0	0
306521	0	0
306522	0	0
306523	0	0
306524	0	0
306525	0	0
306526	0	0
306527	0	0
306528	0	0
306529	0	0
306530	0	0
306531	0	0
306532	0	0
306533	0	0

	5a8bc65990b245e5a138643cd4eb9837	9b98b8c7a33c4b65b9aebfe6a799e6d9 \
0	0	1
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	0	0
7	0	0
8	0	0
9	0	0
10	0	0
11	0	0
12	0	0
13	0	0
14	0	0
15	0	0
16	0	0
17	0	0
18	0	1
19	0	0
20	0	0

21	0	1
22	0	0
23	0	0
24	0	0
25	0	0
26	0	0
27	0	0
28	0	1
29	0	0
...	...	...
306504	0	0
306505	0	0
306506	0	0
306507	0	0
306508	0	0
306509	0	0
306510	0	0
306511	0	0
306512	0	0
306513	0	0
306514	0	0
306515	0	0
306516	0	0
306517	0	0
306518	0	0
306519	0	0
306520	0	0
306521	0	0
306522	0	0
306523	0	0
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306525	0	0
306526	0	0
306527	0	0
306528	0	0
306529	0	0
306530	0	0
306531	0	0
306532	0	0
306533	0	0
	ae264e3637204a6fb9bb56bc8210ddfd	f19421c1d4aa40978ebb69ca19b0e20d \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
5	0	1

6	0	0
7	0	0
8	0	0
9	0	0
10	0	0
11	0	0
12	1	0
13	0	0
14	0	0
15	0	0
16	0	0
17	0	0
18	0	0
19	1	0
20	0	0
21	0	0
22	0	0
23	0	0
24	0	0
25	0	0
26	0	1
27	1	0
28	0	0
29	0	0
...	...	...
306504	0	0
306505	0	0
306506	0	0
306507	0	0
306508	0	0
306509	0	0
306510	0	0
306511	0	0
306512	0	0
306513	0	0
306514	0	0
306515	0	0
306516	0	0
306517	0	0
306518	0	0
306519	0	0
306520	0	0
306521	0	0
306522	0	0
306523	0	0
306524	0	0
306525	0	0
306526	0	0

306527	0	0
306528	0	0
306529	0	0
306530	0	0
306531	0	0
306532	0	0
306533	0	0

fafdcd668e3743c1bb461111dcafc2a4

0	0
1	0
2	0
3	1
4	0
5	0
6	0
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8	0
9	0
10	0
11	0
12	0
13	0
14	0
15	1
16	0
17	0
18	0
19	0
20	0
21	0
22	0
23	0
24	0
25	0
26	0
27	0
28	0
29	1

...	...
306504	0
306505	0
306506	1
306507	0
306508	0
306509	1
306510	0
306511	0

306512	0
306513	0
306514	0
306515	0
306516	0
306517	0
306518	0
306519	0
306520	0
306521	0
306522	0
306523	0
306524	0
306525	0
306526	0
306527	1
306528	0
306529	0
306530	0
306531	0
306532	0
306533	0

[306534 rows x 29 columns]

Dropping some columns and selecting others as features

```
In [138]: tran.columns
```

```
Out[138]: Index(['event', 'person', 'time', 'offer_id', 'reward', 'amount',
                'offer_type_map', 'age_offer', 'map_gender_offer', 'income',
                'offer completed', 'offer received', 'offer viewed', 'transaction',
                'NA', 'bogo', 'discount', 'informational', '',
                '0b1e1539f2cc45b7b9fa7c272da2e1d7', '2298d6c36e964ae4a3e7e9706d1fb8c2',
                '2906b810c7d4411798c6938adc9daaa5', '3f207df678b143eea3cee63160fa8bed',
                '4d5c57ea9a6940dd891ad53e9dbe8da0', '5a8bc65990b245e5a138643cd4eb9837',
                '9b98b8c7a33c4b65b9aebfe6a799e6d9', 'ae264e3637204a6fb9bb56bc8210ddfd',
                'f19421c1d4aa40978ebb69ca19b0e20d', 'fafdc668e3743c1bb461111dcafc2a4'],
                dtype='object')
```

The following columns are selected as target variables

```
In [139]: targets = tran[["offer completed","offer received","offer viewed","transaction"]]
```

```
In [ ]:
```

```
In [140]: features=tran.drop(["person","event","offer_id","offer_type_map","offer completed","of
```

```
In [141]: features=features.drop(['','NA'],axis=1)
```

```

In [142]: data=pd.get_dummies(transcript['map_gender_offer'])

In [143]: features=features.join(data)

In [144]: features=features.drop(["map_gender_offer"],axis=1)

In [ ]:

In [145]: remove_s=lambda x:x[:-1]
          features['age_offer']=features["age_offer"].apply(remove_s)

In [146]: features['age_offer']=features['age_offer'].astype(int)

In [147]: features

```

```

Out[147]:

```

	time	reward	amount	age_offer	income	bogo	discount	\
0	0	0	0	70	100000.000000	1	0	
1	0	0	0	110	65404.991568	0	1	
2	0	0	0	60	70000.000000	0	1	
3	0	0	0	110	65404.991568	0	1	
4	0	0	0	110	65404.991568	1	0	
5	0	0	0	60	53000.000000	1	0	
6	0	0	0	110	65404.991568	0	1	
7	0	0	0	50	51000.000000	0	0	
8	0	0	0	60	57000.000000	0	1	
9	0	0	0	60	71000.000000	0	1	
10	0	0	0	110	65404.991568	0	1	
11	0	0	0	110	65404.991568	0	1	
12	0	0	0	60	100000.000000	1	0	
13	0	0	0	70	71000.000000	0	0	
14	0	0	0	80	53000.000000	0	1	
15	0	0	0	40	69000.000000	0	1	
16	0	0	0	50	88000.000000	0	1	
17	0	0	0	110	65404.991568	0	1	
18	0	0	0	50	41000.000000	1	0	
19	0	0	0	20	70000.000000	1	0	
20	0	0	0	90	89000.000000	0	1	
21	0	0	0	40	33000.000000	1	0	
22	0	0	0	60	57000.000000	1	0	
23	0	0	0	110	65404.991568	0	1	
24	0	0	0	20	63000.000000	0	1	
25	0	0	0	110	65404.991568	0	1	
26	0	0	0	70	40000.000000	1	0	
27	0	0	0	20	30000.000000	1	0	
28	0	0	0	40	33000.000000	1	0	
29	0	0	0	110	65404.991568	0	1	
...	...	...	...	...	...	...	...	
306504	714	0	4	70	75000.000000	0	0	
306505	714	0	4	110	65404.991568	0	0	

306506	714	2	0	110	65404.991568	0	1
306507	714	0	0	60	64000.000000	0	1
306508	714	0	1	30	39000.000000	0	0
306509	714	2	0	30	39000.000000	0	1
306510	714	0	14	30	68000.000000	0	0
306511	714	0	2	60	63000.000000	0	0
306512	714	0	6	30	62000.000000	0	0
306513	714	0	12	30	65000.000000	0	0
306514	714	0	8	40	56000.000000	0	0
306515	714	0	2	60	42000.000000	0	0
306516	714	0	9	50	53000.000000	0	0
306517	714	0	11	20	48000.000000	0	0
306518	714	0	40	100	82000.000000	0	0
306519	714	0	31	60	84000.000000	0	0
306520	714	0	1	30	61000.000000	0	0
306521	714	0	17	40	64000.000000	0	0
306522	714	0	4	80	59000.000000	0	0
306523	714	0	18	40	69000.000000	0	0
306524	714	0	25	40	68000.000000	0	0
306525	714	0	43	50	95000.000000	0	0
306526	714	0	22	40	80000.000000	0	0
306527	714	2	0	40	80000.000000	0	1
306528	714	0	2	110	65404.991568	0	0
306529	714	0	1	60	47000.000000	0	0
306530	714	0	9	50	62000.000000	0	0
306531	714	0	3	60	52000.000000	0	0
306532	714	0	3	50	40000.000000	0	0
306533	714	0	4	110	65404.991568	0	0

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16	0	1	
17	0	0	



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306508	0	0
306509	0	0
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306511	0	0
306512	0	0
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306514	0	0
306515	0	0
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306530	0	0
306531	0	0
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306533	0	0

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306532	0	0
306533	0	0

	9b98b8c7a33c4b65b9aebfe6a799e6d9	ae264e3637204a6fb9bb56bc8210ddfd \
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306532	0	0
306533	0	0
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7	0	0 0
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16	0	0 1
17	0	0 0
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24	0	0 1
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306504	0	0 0
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306510	0	0 1
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12	1	0	0
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19	1	0	0
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```

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```

```
[306534 rows x 22 columns]
```

Normalising all the columns having large values so that they do not dominate in the model and all rows are equal

```
In [148]: from sklearn.preprocessing import MinMaxScaler
```

```

scaler = MinMaxScaler()
to_normalize = ['time', 'amount', 'reward', 'income', 'age_offer']

features[to_normalize] = scaler.fit_transform(features[to_normalize])
features.head()

```

```

Out[148]:   time  reward  amount  age_offer  income  bogo  discount  informational  \
0    0.0    0.0    0.0        0.6  0.777778    1         0          0
1    0.0    0.0    0.0        1.0  0.393389    0         1          0
2    0.0    0.0    0.0        0.5  0.444444    0         1          0
3    0.0    0.0    0.0        1.0  0.393389    0         1          0
4    0.0    0.0    0.0        1.0  0.393389    1         0          0

      0b1e1539f2cc45b7b9fa7c272da2e1d7  2298d6c36e964ae4a3e7e9706d1fb8c2  ...  \
0                                     0                                     0  ...
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```



4	0	0 ...
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4	1	0
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0	1	0
1	0	0
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3	0	0
4	0	0
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3	0	1 0 0
4	0	0 0 0
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0	0	0
1	1	0
2	0	0
3	1	0
4	1	0

[5 rows x 22 columns]

```
In [149]: from sklearn.model_selection import train_test_split, GridSearchCV
```

```
In [150]: X_train, X_test, y_train, y_test = train_test_split(features, targets, random_state=0)
```

```
In [151]: print('Training Features Shape:', X_train.shape)
           print('Training Labels Shape:', y_train.shape)
           print('Testing Features Shape:', X_test.shape)
           print('Testing Labels Shape:', y_test.shape)
```

Training Features Shape: (229900, 22)

Training Labels Shape: (229900, 4)

Testing Features Shape: (76634, 22)

Testing Labels Shape: (76634, 4)

Model using Decision tree classifier gets an accuracy of 95.5% on test set

```
In [157]: from sklearn.tree import DecisionTreeClassifier
          from sklearn.metrics import accuracy_score
          dt = DecisionTreeClassifier(criterion='gini', splitter='best', max_depth=None, min_samples_split=2,
                                     class_weight=None, presort='deprecated')

          dt.fit(X_train, y_train)
          yt_pred=dt.predict(X_train)
          print(f'Accuracy of Decision Tree classifier on training set: {accuracy_score(y_train, yt_pred)}')
          y_pred=dt.predict(X_test)
          print(f'Prediction Accuracy: {accuracy_score(y_test, y_pred)*100}%')
```

Accuracy of Decision Tree classifier on training set: 95.64984775989561%.  
 Prediction Accuracy: 95.56071717514419%

Model using RandomForestClassifier gets an accuracy of 91.3% on test set

```
In [158]: from sklearn.ensemble import RandomForestClassifier
          from sklearn.metrics import accuracy_score
          rc = RandomForestClassifier(n_estimators=200, criterion='gini', max_depth=None, min_samples_split=2)

          rc.fit(X_train, y_train)
          yt_pred=rc.predict(X_train)
          print(f'Accuracy of Decision Tree classifier on training set: {accuracy_score(y_train, yt_pred)}')
          y_pred=rc.predict(X_test)
          print(f'Prediction Accuracy: {accuracy_score(y_test, y_pred)*100}%')
```

building tree 1 of 200

[Parallel(n\_jobs=1)]: Done 1 out of 1 | elapsed: 0.3s remaining: 0.0s

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building tree 200 of 200

[Parallel(n\_jobs=1)]: Done 200 out of 200 | elapsed: 1.2min finished  
[Parallel(n\_jobs=1)]: Done 1 out of 1 | elapsed: 0.1s remaining: 0.0s  
[Parallel(n\_jobs=1)]: Done 200 out of 200 | elapsed: 13.4s finished  
[Parallel(n\_jobs=1)]: Done 1 out of 1 | elapsed: 0.0s remaining: 0.0s

Accuracy of Decision Tree classifier on training set: 91.99869508481949%.

Prediction Accuracy: 91.2480100216614%

[Parallel(n\_jobs=1)]: Done 200 out of 200 | elapsed: 4.1s finished

Model built using Kneighbours Classifier reached an accuracy of 86% on test set

```
In [159]: from sklearn.neighbors import KNeighborsClassifier
          from sklearn.metrics import accuracy_score
          kn = KNeighborsClassifier()

          kn.fit(X_train, y_train)
          yt_pred=kn.predict(X_train)
          print(f'Accuracy of Decision Tree classifier on training set: {accuracy_score(y_train, yt_pred)}%')
          y_pred=kn.predict(X_test)
          print(f'Prediction Accuracy: {accuracy_score(y_test, y_pred)*100}%')
```

Accuracy of Decision Tree classifier on training set: 90.72422792518486%.

Prediction Accuracy: 86.0049064383955%

We can see that the best accuracy is achieved with decision tree classifier of 95.5% on test set  
Following cells depict the use of GridSearchCV for improving model

```
In [163]: from sklearn.model_selection import GridSearchCV
          min_samples_leaf=[10,20,40,50,100]
          min_samples_split=[10,30,50,40,100]
          min_weight_fraction_leaf=[0.0,0.1,0.4]
          min_impurity_decrease=[0.0,0.2]
          max_features=["auto","sqrt"]
          param_grid = dict( min_weight_fraction_leaf=min_weight_fraction_leaf,min_samples_leaf=
                               min_samples_split,max_features=max_features,min_impurity_decrease=min_impurity_decrease)

          grid = GridSearchCV(estimator=dt, param_grid=param_grid,cv=3,n_jobs=-1)

In [ ]: grid_result = grid.fit(X_train, y_train)

In [ ]: print(f'Best Score: {grid_result.best_score_}')
          print(f'Best params: {grid_result.best_params_}')
```

## Conclusion

An attempt has been made to analyze the dataset of Starbucks and understand the data and make model to predict how will a customer take the offer whether the offer will be received or not and whether it will be completed. Firstly the data is analysed and explored and relation between different variables is understood with the help of graphs. The distribution of variables in the data is set, what types of customer base is there and gender wise distribution of the customer base based on their income and how much offers do they receive do they complete the offer or not is analysed. It is found that Females complete offers compared to males with 56% completion of what they receive compared to 43.18% among males but males receive more offers than females.

The scenario completely changes for transactions which is 72794 among males and 49382 among females. Further exploration was made on which offer is being received better by the customer. Hence females could be given more offers further offer id fafdcd668e3743c1bb461111dcafc2a4 should be more distributed compared to others since it is completed more number of times.

#### 'Improvements

Improvement can be made on how NAN values are filled and completing the NAN values, further location based data could be used for location specific recommendations. All these could help us to give more personalised recommendation to customers

In [ ]: