Starbucks Capstone Challenge

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.

Your task is to combine transaction, demographic and offer data to determine which demographic groups respond best to which offer type. This data set is a simplified version of the real Starbucks app because the underlying simulator only has one product whereas Starbucks actually sells dozens of products.

Every offer has a validity period before the offer expires. As an example, a BOGO offer might be valid for only 5 days. You'll see in the data set that informational offers have a validity period even though these ads are merely providing information about a product; 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.

You'll be 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.

Keep in mind as well that someone using the app might make a purchase through the app without having received an offer or seen an offer.

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.

Cleaning

This makes data cleaning especially important and tricky.

You'll also want to take into account that some demographic groups will make purchases even if they don't receive an offer. 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. You'll want to try to assess what a certain demographic group will buy when not receiving any offers.

Final Advice

Because this is a capstone project, you are free to analyze the data any way you see fit. For example, you could build a machine learning model that predicts how much someone will spend based on demographics and offer type. Or you could build a model that predicts whether or not someone will respond to an offer. Or, you don't need to build a machine learning model at all. You could develop a set of heuristics that determine what offer you should send to each customer (i.e., 75 percent of women customers who were 35 years old responded to offer A vs 40 percent from the same demographic to offer B, so send offer A).

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

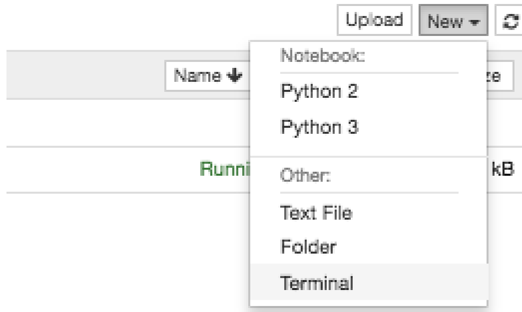
- age (int) - age of the customer
- became_member_on (int) - date when customer created an app account
- gender (str) - gender of the customer (note some entries contain 'O' for other rather than M or F)
- id (str) - customer id
- income (float) - customer's income

transcript.json

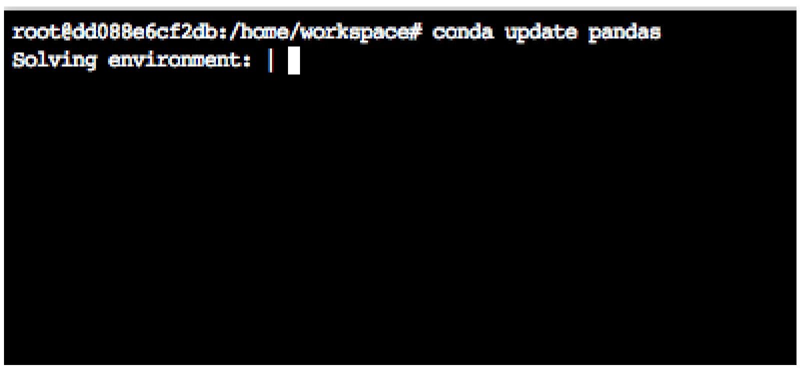
- event (str) - record description (ie transaction, offer received, offer viewed, etc.)
- person (str) - customer id
- time (int) - time in hours since start of test. The data begins at time t=0
- value - (dict of strings) - either an offer id or transaction amount depending on the record

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 termnal 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.

Importing Library and reading files

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import math
import json
import datetime
import matplotlib.pyplot as plt

from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestRegressor
sns.set()

%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=Tru
e)
```

Tacking a snap pick to data

In [2]:
```
portfolio.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 6 columns):
channels      10 non-null object
difficulty    10 non-null int64
duration      10 non-null int64
id            10 non-null object
offer_type    10 non-null object
reward        10 non-null int64
dtypes: int64(3), object(3)
memory usage: 560.0+ bytes
```

In [3]:
```
profile.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17000 entries, 0 to 16999
Data columns (total 5 columns):
age                 17000 non-null int64
became_member_on    17000 non-null int64
gender              14825 non-null object
id                  17000 non-null object
income              14825 non-null float64
dtypes: float64(1), int64(2), object(2)
memory usage: 664.1+ KB
```

In [4]:
```
transcript.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 306534 entries, 0 to 306533
Data columns (total 4 columns):
event     306534 non-null object
person    306534 non-null object
time      306534 non-null int64
value     306534 non-null object
dtypes: int64(1), object(3)
memory usage: 9.4+ MB
```

First portfolio dataset

In [5]:
```
portfolio.head()
```

Out[5]:

	channels	difficulty	duration	id	offer_type	reward
0	[email, mobile, social]	10	7	ae264e3637204a6fb9bb56bc8210ddfd	bogo	10
1	[web, email, mobile, social]	10	5	4d5c57ea9a6940dd891ad53e9dbe8da0	bogo	10
2	[web, email, mobile]	0	4	3f207df678b143eea3cee63160fa8bed	informational	0
3	[web, email, mobile]	5	7	9b98b8c7a33c4b65b9aebfe6a799e6d9	bogo	5
4	[web, email]	20	10	0b1e1539f2cc45b7b9fa7c272da2e1d7	discount	5

In [6]:
```
print('The number of columns {} and the number of rows are {}'.format(portfoli
o.shape[1],portfolio.shape[0]))
```

```
The number of columns 6 and the number of rows are 10
```

In [7]:
```
portfolio.describe()
```

Out[7]:

	difficulty	duration	reward
count	10.000000	10.000000	10.000000
mean	7.700000	6.500000	4.200000
std	5.831905	2.321398	3.583915
min	0.000000	3.000000	0.000000
25%	5.000000	5.000000	2.000000
50%	8.500000	7.000000	4.000000
75%	10.000000	7.000000	5.000000
max	20.000000	10.000000	10.000000

In [8]:
```
#checking for null value in dataset
portfolio.isnull().sum()
```

Out[8]:
```
channels      0
difficulty    0
duration      0
id            0
offer_type    0
reward        0
dtype: int64
```

In [9]:
```
#checking for duplicate value in dataset
portfolio.columns.duplicated().sum()
```

Out[9]:
```
0
```

In [10]:
```
# checking the number of unique offers
portfolio['id'].nunique()
```

Out[10]:
```
10
```

In [11]:
```
# counting the offers by their type
portfolio.groupby('offer_type')['id'].count()
```

Out[11]:
```
offer_type
bogo             4
discount         4
informational    2
Name: id, dtype: int64
```

The above preliminary Exploration for the Portfolio Dataset shows the following:
The dataset has 6 columns and 10 rows.
This dataset has no null values nor duplicates.
There are three types of offers : 'bogo', 'informational' and 'discount'.
The 'difficulty' column unit is dollars , which does not reflect how difficult to be rewarded. Rescaling this feature is a useful step to do. This needs to be done before Modeling.

secound profile dataset

In [12]:
```
profile.head()
```

Out[12]:

	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 [13]:
```
print('The number of columns {} and the number of rows are {}'.format(profile.
shape[1],profile.shape[0]))
```

```
The number of columns 5 and the number of rows are 17000
```

In [14]:
```
profile.describe()
```

Out[14]:

	age	became_member_on	income
count	17000.000000	1.700000e+04	14825.000000
mean	62.531412	2.016703e+07	65404.991568
std	26.738580	1.167750e+04	21598.299410
min	18.000000	2.013073e+07	30000.000000
25%	45.000000	2.016053e+07	49000.000000
50%	58.000000	2.017080e+07	64000.000000
75%	73.000000	2.017123e+07	80000.000000
max	118.000000	2.018073e+07	120000.000000

In [15]:
```
#checking for null value in dataset
profile.isnull().sum()
```

Out[15]:
```
age                    0
became_member_on       0
gender              2175
id                     0
income              2175
dtype: int64
```

In [16]:
```
#checking for duplicate value in dataset
profile.columns.duplicated().sum()
```

Out[16]:
```
0
```

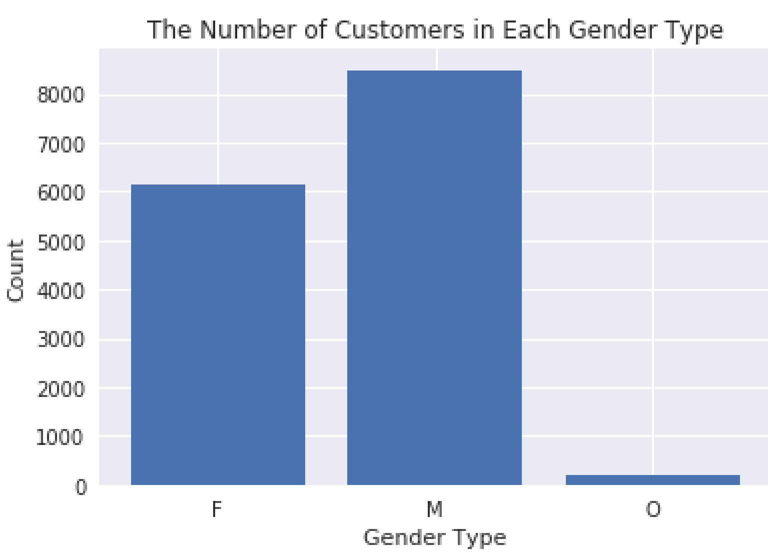
In [17]:
```
#checking unique customer
len(profile['id'].unique())
```

Out[17]:
```
17000
```

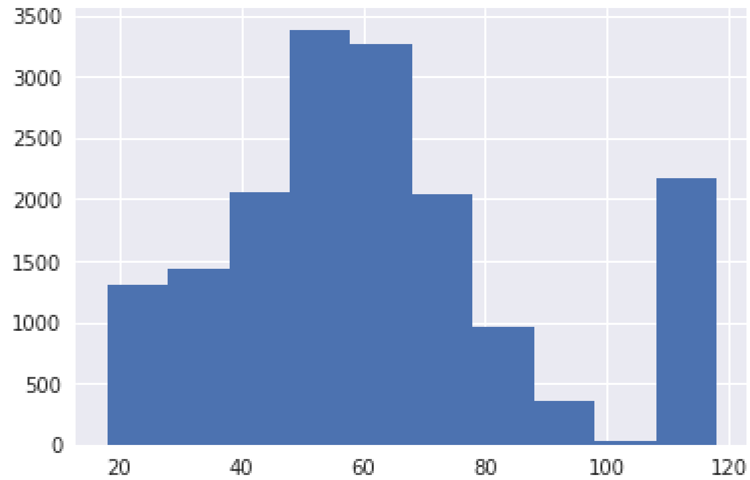
In [18]:
```
#finding count of gender categories
profile.gender.value_counts()
```

Out[18]:
```
M    8484
F    6129
O     212
Name: gender, dtype: int64
```

In [19]:
```
profile_gender_counts = profile.gender.value_counts()
x = ['M','F','O']
data = profile_gender_counts
plt.bar(x,height = data);
plt.xlabel('Gender Type');
plt.ylabel('Count');
plt.title('The Number of Customers in Each Gender Type');
```



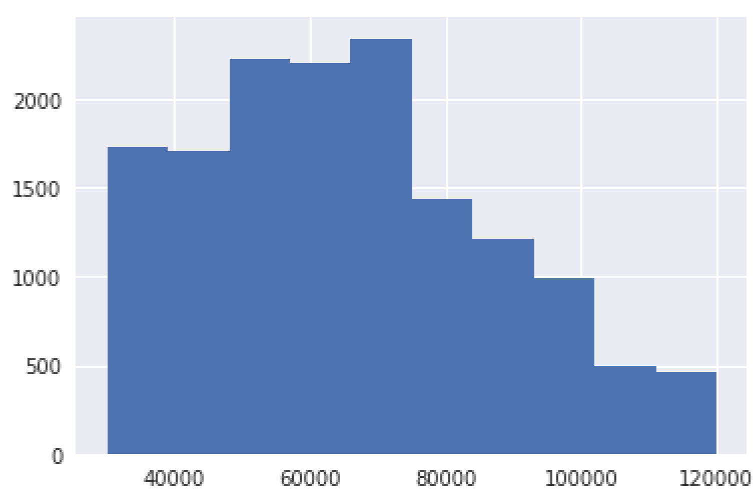
In [20]:
```
#checking age columns
plt.hist(profile['age'], bins=10);
```



In [21]:
```
profile['age'].describe()
```

Out[21]:
```
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
```

In [22]:
```
# checking income columns
profile['income'].hist();
```



The above preliminary Exploration for the profile Dataset shows the following:
The dataset has 5 columns and 17000 rows.
This dataset has no duplicates.
The dataset has 2175 missing values on each of: ‘gender’, ’income’ variables.
We can say that we have more man than women in this dataset.
The median of costmer age is 58 years old, also we can found that we have a maximum 118.

third Transcript dataset

In [23]:
```
transcript.head()
```

Out[23]:

	event	person	time	value
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	0	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}
1	offer received	a03223e636434f42ac4c3df47e8bac43	0	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
2	offer received	e2127556f4f64592b11af22de27a7932	0	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}
3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	0	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}
4	offer received	68617ca6246f4fbc85e91a2a49552598	0	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}

In [24]:
```
print('The number of columns {} and the number of rows are {}'.format(transcri
pt.shape[1],transcript.shape[0]))
```

```
The number of columns 4 and the number of rows are 306534
```

In [25]:
```
#checking for null value in dataset
transcript.isnull().sum()
```

Out[25]:
```
event     0
person    0
time      0
value     0
dtype: int64
```

In [26]:
```
#checking for duplicate value in dataset
transcript.columns.duplicated().sum()
```

Out[26]:
```
0
```

In [27]:
```
#Type of event counts
transcript.event.value_counts()
```

Out[27]:
```
transaction        138953
offer received      76277
offer viewed        57725
offer completed     33579
Name: event, dtype: int64
```

In [28]:
```
transcript[transcript['event']=='transaction']
```

Out[28]:

	event	person	time	value
12654	transaction	02c083884c7d45b39cc68e1314fec56c	0	{'amount': 0.8300000000000001}
12657	transaction	9fa9ae8f57894cc9a3b8a9bbe0fc1b2f	0	{'amount': 34.56}
12659	transaction	54890f68699049c2a04d415abc25e717	0	{'amount': 13.23}
12670	transaction	b2f1cd155b864803ad8334cdf13c4bd2	0	{'amount': 19.51}
12671	transaction	fe97aa22dd3e48c8b143116a8403dd52	0	{'amount': 18.97}
12678	transaction	629fc02d56414d91bca360decdfa9288	0	{'amount': 33.9}
12686	transaction	bbeb54e861614fc7b22a8844f72dca6c	0	{'amount': 0.22}
12687	transaction	a97e6f33219c432db82acfa0d19c602d	0	{'amount': 18.59}
12691	transaction	676506bad68e4161b9bbaffeb039626b	0	{'amount': 18.01}
12696	transaction	8f7dd3b2afe14c078eb4f6e6fe4ba97d	0	{'amount': 19.11}
12706	transaction	4cbe33c601a5407f8202086565c55111	0	{'amount': 36.19}
12709	transaction	b432b74402bb4981a4651c8df1670365	0	{'amount': 6.46}
12711	transaction	a04fcfd571034456aaa6d56c0a3fd9b6	0	{'amount': 5.02}
12716	transaction	227f2d69e46a4899b70d48182822cff6	0	{'amount': 28.39}
12720	transaction	bb0f25e23a4c4de6a645527c275cd594	0	{'amount': 28.08}
12724	transaction	c2c72ce6038644c797208046d1e3498a	0	{'amount': 0.75}
12738	transaction	7ca349e55ff544c7a13addfdea2e2c06	0	{'amount': 1.02}
12743	transaction	d72d201be5794279aa716d8ad82b8d90	0	{'amount': 13.57}
12756	transaction	ad80753fc9e0485c9e6b1cc9478d827f	0	{'amount': 10.22}
12763	transaction	73ffefd41e9a4ca3ab26b2b3697c6eb7	0	{'amount': 31.42}
12766	transaction	3e621194f72e40d7a0b695ee9b7c38b7	0	{'amount': 27.89}
12768	transaction	1f5c961416e64c5d88098b02b1bdf246	0	{'amount': 4.2}
12775	transaction	3bcc51fdde354eb1949c813dbc905182	0	{'amount': 13.05}
12777	transaction	ed46fca6de7042478b411690878dc069	0	{'amount': 1.16}
12779	transaction	b860d355ef6e4c66b5d5a837c56ef32d	0	{'amount': 38.38}
12781	transaction	4ad3748475204cf99571183f05b5e2f7	0	{'amount': 4.08}
12783	transaction	99297ea01107436fa8c2e2bc86f55d89	0	{'amount': 5.78}
12785	transaction	24115a61df25473e84a8a03f3c98de1a	0	{'amount': 14.27}
12794	transaction	7195944f0cc34115b0a5e7b4a62055f2	0	{'amount': 11.52}
12797	transaction	afce4cf8194f4e90a3e92da941a23601	0	{'amount': 13.93}
...	...	...	...	...
306500	transaction	f0ffaed9279946f1bc29614a234f1ee1	714	{'amount': 1.43}
306501	transaction	93907d06a946424ba630487fe7aeafd1	714	{'amount': 28.03}
306502	transaction	588ceea482344c3ab6845c83aaed4ac0	714	{'amount': 1.08}
306503	transaction	a97208c5be42445d9949e82e0f70f622	714	{'amount': 5.8}

	event	person	time	value
306504	transaction	8524d450673b4c24869b6c94380006de	714	{'amount': 4.89}
306505	transaction	b895c57e8cd047a8872ce02aa54759d6	714	{'amount': 4.48}
306508	transaction	8431c16f8e1d440880db371a68f82dd0	714	{'amount': 1.19}
306510	transaction	ba620885e51c4b0ea64a4f61daad494f	714	{'amount': 14.31}
306511	transaction	a1a8f40407c444cc848468275308958a	714	{'amount': 2.37}
306512	transaction	8d80970192fa496f99d6b45c470a4b60	714	{'amount': 6.92}
306513	transaction	bde275066f3c4fa0bff3093e3b866a2c	714	{'amount': 12.73}
306514	transaction	f1e4fd36e5a0446f83861308bddf6945	714	{'amount': 8.2}
306515	transaction	0b64be3b241c4407a5c9a71781173829	714	{'amount': 2.6}
306516	transaction	86d03d35d7e0434b935e7743e83be3a0	714	{'amount': 9.2}
306517	transaction	3408fd05c781401f8442fb6dbaaea9c7	714	{'amount': 11.7}
306518	transaction	1593d617fac246ef8e50dbb0ffd77f5f	714	{'amount': 40.67}
306519	transaction	f1b31d07b5d84f69a2d5f1d07843989e	714	{'amount': 31.13}
306520	transaction	2ce987015ec0404a97ba333e8e814090	714	{'amount': 1.6400000000000001}
306521	transaction	2e33545f0a764d27b2ccff95fc8d72c4	714	{'amount': 17.35}
306522	transaction	d1c4500ace2e45e9a45d3cd2fccac8d8	714	{'amount': 4.42}
306523	transaction	b65affd9e07346a1906364a396950e3d	714	{'amount': 18.35}
306524	transaction	d613ca9c59dd42f497bdbf6178da54a7	714	{'amount': 25.14}
306525	transaction	eec70ab28af74a22a4aeb889c0317944	714	{'amount': 43.58}
306526	transaction	24f56b5e1849462093931b164eb803b5	714	{'amount': 22.64}
306528	transaction	5ca2620962114246ab218fc648eb3934	714	{'amount': 2.2}
306529	transaction	b3a1272bc9904337b331bf348c3e8c17	714	{'amount': 1.5899999999999999}
306530	transaction	68213b08d99a4ae1b0dcb72aebd9aa35	714	{'amount': 9.53}
306531	transaction	a00058cf10334a308c68e7631c529907	714	{'amount': 3.61}
306532	transaction	76ddbd6576844afe811f1a3c0fbb5bec	714	{'amount': 3.5300000000000002}
306533	transaction	c02b10e8752c4d8e9b73f918558531f7	714	{'amount': 4.05}

138953 rows × 4 columns

The above Exploration for the Transcript Dataset shows the following:
The dataset has 4 columns and 306,534 rows.
The dataset has no duplicated rows nor missing values.
The ‘value’ column is a dictionary.
There are four types of events in this dataset: ‘transaction’, ’ offer received’, ‘offer viewed’ and ‘offer completed’.
All the events that are classified as ‘transaction’ do not have an ‘offerid’ within its ‘value’ column.

Data Processing

For Portfolio Dataset:

- Rename 'id' column to 'offer_id'.
- Change the unit of 'duration' column from days to hours.
- Rename 'duration' column to 'duration_h' representing that the unit of measurment is 'hours'
- Create dummy variables from the 'channels' column
- Replace the 'offer_id' by more easy ids.
- Replace the 'offer_type' by integers representing each offer type as follow:
bogo = 1
discount = 2
informational = 3
- Normalize 'difficulty' and 'reward' features using the MinMaxScaler

In [29]:
```
# creating a copy of the dataset
clean_portfolio = portfolio.copy()
```

- Rename 'id' column to 'offer_id'

In [30]:
```
clean_portfolio.rename(columns={'id':'offer_id'},inplace=True)
```

- Change the unit of 'duration' column from days to hours

In [31]:
```
clean_portfolio['duration'] = clean_portfolio['duration']*24
```

- Rename 'duration' column to 'duration_h' representing that the unit of measurment is 'hours'

In [32]:
```
clean_portfolio.rename(columns={'duration':'duration_h'},inplace=True)
```

- Create dummy variables from the 'channels' column

In [33]:
```
#creating the dummy
clean_portfolio['channel_email'] = clean_portfolio['channels'].apply(lambda x: 1 if 'email' in x else 0)
clean_portfolio['channel_mobile'] = clean_portfolio['channels'].apply(lambda x: 1 if 'mobile' in x else 0)
clean_portfolio['channel_social'] = clean_portfolio['channels'].apply(lambda x: 1 if 'social' in x else 0)
clean_portfolio['channel_web'] = clean_portfolio['channels'].apply(lambda x: 1 if 'web' in x else 0)
```

In [34]:
```
#takeing a look of change
clean_portfolio[['channels','channel_email','channel_mobile','channel_web','channel_social']].head()
```

Out[34]:

	channels	channel_email	channel_mobile	channel_web	channel_social
0	[email, mobile, social]	1	1	0	1
1	[web, email, mobile, social]	1	1	1	1
2	[web, email, mobile]	1	1	1	0
3	[web, email, mobile]	1	1	1	0
4	[web, email]	1	0	1	0

In [35]:
```
#droping columns
clean_portfolio.drop('channels', axis=1, inplace=True)
```

In [36]:
```
#checking dataset after creating changes
clean_portfolio.head()
```

Out[36]:

	difficulty	duration_h	offer_id	offer_type	reward	channel_email
0	10	168	ae264e3637204a6fb9bb56bc8210ddfd	bogo	10	1
1	10	120	4d5c57ea9a6940dd891ad53e9dbe8da0	bogo	10	1
2	0	96	3f207df678b143eea3cee63160fa8bed	informational	0	1
3	5	168	9b98b8c7a33c4b65b9aebfe6a799e6d9	bogo	5	1
4	20	240	0b1e1539f2cc45b7b9fa7c272da2e1d7	discount	5	1

- Replace the 'offer_id' by more easy ids

In [37]:
```
labels_offer_id = clean_portfolio['offer_id'].astype('category').cat.categories.tolist() # replacing the 'offer_id' by more easy ids
replace_map_comp_offer_id = {'offer_id' : {k: v for k,v in zip(labels_offer_id,list(range(1,len(labels_offer_id)+1)))}}
clean_portfolio.replace(replace_map_comp_offer_id, inplace=True)# replacing the categorical values in the 'offer_id' column by numberical values
```

In [38]:
```
clean_portfolio
```

Out[38]:

	difficulty	duration_h	offer_id	offer_type	reward	channel_email	channel_mobile	channel_s
0	10	168	8	bogo	10	1	1	
1	10	120	5	bogo	10	1	1	
2	0	96	4	informational	0	1	1	
3	5	168	7	bogo	5	1	1	
4	20	240	1	discount	5	1	0	
5	7	168	2	discount	3	1	1	
6	10	240	10	discount	2	1	1	
7	0	72	6	informational	0	1	1	
8	5	120	9	bogo	5	1	1	
9	10	168	3	discount	2	1	1	

- Replace the 'offer_type' by integers representing each offer type as follow: bogo discount informational

In [39]:
```
labels_offer_type = clean_portfolio['offer_type'].astype('category').cat.categ
ories.tolist()
replace_map_comp_offer_type = {'offer_type' : {k: v for k,v in zip(labels_offe
r_type,list(range(1,len(labels_offer_type)+1)))}}
clean_portfolio.replace(replace_map_comp_offer_type, inplace=True)
```

In [40]:
```
clean_portfolio
```

Out[40]:

	difficulty	duration_h	offer_id	offer_type	reward	channel_email	channel_mobile	channel_so
0	10	168	8	1	10	1	1	
1	10	120	5	1	10	1	1	
2	0	96	4	3	0	1	1	
3	5	168	7	1	5	1	1	
4	20	240	1	2	5	1	0	
5	7	168	2	2	3	1	1	
6	10	240	10	2	2	1	1	
7	0	72	6	3	0	1	1	
8	5	120	9	1	5	1	1	
9	10	168	3	2	2	1	1	

- Normalize 'difficulty' and 'reward' features using the MinMaxScaler

In [41]:
```
# Initialize a scaler, then apply it to the features
scaler = MinMaxScaler() # default=(0, 1)
numerical = ['difficulty','reward']

#features_log_minmax_transform
clean_portfolio[numerical] = scaler.fit_transform(clean_portfolio[numerical])

# Show an example of a record with scaling applied
clean_portfolio.head()
```

Out[41]:

	difficulty	duration_h	offer_id	offer_type	reward	channel_email	channel_mobile	channel_so
0	0.50	168	8	1	1.0	1	1	
1	0.50	120	5	1	1.0	1	1	
2	0.00	96	4	3	0.0	1	1	
3	0.25	168	7	1	0.5	1	1	
4	1.00	240	1	2	0.5	1	0	

For Profile Dataset:

In [42]:
```
#taken a copy of the dataset
clean_profile = profile.copy()
```

In [43]:
```
clean_profile.head()
```

Out[43]:

	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

will begin with ID columns:

- Will change columns name
- will replace the value of customer id with somthing numerical and easy to deal with

In [44]:
```
# renaming 'id' column name to 'customer_id'.
clean_profile.rename(columns={'id':'customer_id'},inplace=True)
```

In [45]:
```
# replacing the 'customer_id' string values  with easiest numerical values
labels_customer_id = clean_profile['customer_id'].astype('category').cat.categories.tolist()
replace_map_comp_customer_id = {'customer_id' : {k: v for k,v in zip(labels_customer_id,list(range(1,len(labels_customer_id)+1)))}}
clean_profile.replace(replace_map_comp_customer_id, inplace=True)
```

In [46]:
```
clean_profile.head()
```

Out[46]:

	age	became_member_on	gender	customer_id	income
0	118	20170212	None	6962	NaN
1	55	20170715	F	399	112000.0
2	118	20180712	None	3747	NaN
3	75	20170509	F	7997	100000.0
4	118	20170804	None	10736	NaN

Then age columns:

- Will replace the age 118 with nan
- droping rows with null value
- changing the datatype for age and income columns
- creating an age categories and range
  teenager= 1
  young-adult= 2
  adult= 3
  elderly= 4

In [47]:
```
# replacing the age = 118 by NaN value
clean_profile['age'] = clean_profile['age'].apply(lambda x: np.nan if x == 118 else x)
```

In [48]:
```
# dropping rows with NaNs in 'age', 'gender' and 'income' columns
clean_profile.dropna(inplace=True)
```

In [49]:
```
# changing the datatype of 'age' and 'income' columns to 'int'
clean_profile[['age','income']] = clean_profile[['age','income']].astype(int)
```

In [50]:
```
# creating a new column representing the age group to which the customer belongs
clean_profile['age_group'] = pd.cut(clean_profile['age'], bins=[17, 22, 35, 60, 103],labels=['teenager', 'young-adult', 'adult', 'elderly'])
```

In [51]:
```
# replacing the 'age_group' categorical labels by numerical labels
labels_age_group = clean_profile['age_group'].astype('category').cat.categorie
s.tolist()
replace_map_comp_age_group = {'age_group' : {k: v for k,v in zip(labels_age_gr
oup,list(range(1,len(labels_age_group)+1)))}}
clean_profile.replace(replace_map_comp_age_group, inplace=True)
```

In [52]:
```
clean_profile.head()
```

Out[52]:

	age	became_member_on	gender	customer_id	income	age_group
1	55	20170715	F	399	112000	3
3	75	20170509	F	7997	100000	4
5	68	20180426	M	15044	70000	4
8	65	20180209	M	3729	53000	4
12	58	20171111	M	3060	51000	3

Then income columns:

- Will have new columns with income group

average = 1

above_average= 2

high= 3

In [53]:
```
# creating a new column representing the income group to which the customer be
longs
clean_profile['income_range'] = pd.cut(clean_profile['income'], bins=[29999, 6
0000, 90000, 120001],labels=['average', 'above-average', 'high'])
```

In [54]:
```
# replacing the 'income_range' categorical labels by numerical labels
labels_income_range = clean_profile['income_range'].astype('category').cat.cat
egories.tolist()
replace_map_comp_income_range = {'income_range' : {k: v for k,v in zip(labels_
income_range,list(range(1,len(labels_income_range)+1)))}}
clean_profile.replace(replace_map_comp_income_range, inplace=True)
```

Then gender columns:

- Will change the string into numeric values

  F = 1

  M = 2

  O = 3

In [55]:
```
labels_gender = clean_profile['gender'].astype('category').cat.categories.toli
st()
replace_map_comp_gender = {'gender' : {k: v for k,v in zip(labels_gender,list
(range(1,len(labels_gender)+1)))}}
clean_profile.replace(replace_map_comp_gender, inplace=True)
```

In [56]:
```
clean_profile.head()
```

Out[56]:

	age	became_member_on	gender	customer_id	income	age_group	income_range
1	55	20170715	1	399	112000	3	3
3	75	20170509	1	7997	100000	4	3
5	68	20180426	2	15044	70000	4	2
8	65	20180209	2	3729	53000	4	1
12	58	20171111	2	3060	51000	3	1

Then became_member_on columns:

- Will change the datatype of the columns into date
- will have new columns with the start member ship year
- will have a new columns that count days since register
- will reindex dataset columns
- then will create a new columns with member type based on membership days :

  new (memebr since 1000 days or less) = 1

  regular (1001 - 1,600 days of membership) = 2

  loyal (more than 1,600 days of membership) = 3

In [57]:
```
# changing the datatype of 'became_member_on' column from int to date
clean_profile['became_member_on'] = pd.to_datetime(clean_profile['became_membe
r_on'], format = '%Y%m%d')
```

In [58]:
```
# adding a new column 'start_year'
clean_profile['membership_year'] = clean_profile['became_member_on'].dt.year
```

In [59]:
```
# adding a new column 'membership_days'
clean_profile['membership_days'] = datetime.datetime.today().date() - clean_pr
ofile['became_member_on'].dt.date
# removing the 'days' unit
clean_profile['membership_days'] = clean_profile['membership_days'].dt.days
```

In [60]:
```
clean_profile.head()
```

Out[60]:

	age	became_member_on	gender	customer_id	income	age_group	income_range	members
1	55	2017-07-15	1	399	112000	3	3	
3	75	2017-05-09	1	7997	100000	4	3	
5	68	2018-04-26	2	15044	70000	4	2	
8	65	2018-02-09	2	3729	53000	4	1	
12	58	2017-11-11	2	3060	51000	3	1	

In [61]:
```
clean_profile['member_type'] = pd.cut(clean_profile['membership_days'], bins=
[390, 1000, 1600, 2500],labels=['new', 'regular', 'loyal'])
labels_member_type = clean_profile['member_type'].astype('category').cat.categ
ories.tolist()
replace_map_comp_member_type = {'member_type' : {k: v for k,v in zip(labels_me
mber_type,list(range(1,len(labels_member_type)+1)))}}
clean_profile.replace(replace_map_comp_member_type, inplace=True)
```

In [62]:
```
clean_profile.drop(columns = ['age','income','became_member_on', 'membership_d
ays'], axis=1, inplace=True)
```

In [63]:
```
clean_profile.head()
```

Out[63]:

	gender	customer_id	age_group	income_range	membership_year	member_type
1	1	399	3	3	2017	3
3	1	7997	4	3	2017	3
5	2	15044	4	2	2018	3
8	2	3729	4	1	2018	3
12	2	3060	3	1	2017	3

In [64]:
```
clean_profile.columns
```

Out[64]:
```
Index(['gender', 'customer_id', 'age_group', 'income_range', 'membership_yea
r',
       'member_type'],
      dtype='object')
```

In [65]:
```
#reindex columns for the dataset
clean_profile = clean_profile.reindex(columns=['customer_id', 'gender', 'age_g
roup', 'income_range', 'member_type','membership_year'])
```

In [66]:
```
clean_profile.head()
```

Out[66]:

	customer_id	gender	age_group	income_range	member_type	membership_year
1	399	1	3	3	3	2017
3	7997	1	4	3	3	2017
5	15044	2	4	2	3	2018
8	3729	2	4	1	3	2018
12	3060	2	3	1	3	2017

Transcript Dataset

In [67]:
```
#take a copy of the dataset
clean_transcript = transcript.copy()
```

In [68]:
```
clean_transcript.rename(columns={'person':'customer_id'},inplace=True) #change
person columns to customer id
clean_transcript.replace(replace_map_comp_customer_id, inplace=True) #change t
he data into numeric values
```

In [69]:
```
clean_transcript.head() #checking dataset
```

Out[69]:

	event	customer_id	time	value
0	offer received	7997	0	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}
1	offer received	10736	0	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
2	offer received	15044	0	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}
3	offer received	9525	0	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}
4	offer received	6940	0	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}

In [70]:
```
# Extract each key that exist in 'value' column to a seperate column.
# getting the different keys  that exists in the 'value' column
keys = []
for idx, row in clean_transcript.iterrows():
    for k in row['value']:
        if k in keys:
            continue
        else:
            keys.append(k)
```

In [71]:
```
keys
```
Out[71]:
```
['offer id', 'amount', 'offer_id', 'reward']
```

In [72]:
```
#create columns and we have to specify the datatype of each of them
clean_transcript['offer_id'] = '' # datatype : string
clean_transcript['amount'] = 0  # datatype : integer
clean_transcript['reward'] = 0  # datatype : integer
```

In [73]:
```
# repeated over clean_transcript dataset and checking 'value' column
# then updating it and using the values to fill in the columns created above
for idx, row in clean_transcript.iterrows():
    for k in row['value']:
        if k == 'offer_id' or k == 'offer id': # b/c 'offer_id' and 'offer id'
are representing the same thing
            clean_transcript.at[idx, 'offer_id'] = row['value'][k]
        if k == 'amount':
            clean_transcript.at[idx, 'amount'] = row['value'][k]
        if k == 'reward':
            clean_transcript.at[idx, 'reward'] = row['value'][k]
```

In [74]:
```
clean_transcript['offer_id'] = clean_transcript['offer_id'].apply(lambda x:
'N/A' if x == '' else x)# filling all the NaNs in the 'offer_id' column with
'N/A' values
clean_transcript.drop('value', axis=1, inplace=True)# dropping the 'value' col
umn
```

In [75]:
```
clean_transcript.head()
```
Out[75]:

	event	customer_id	time	offer_id	amount	reward
0	offer received	7997	0	9b98b8c7a33c4b65b9aebfe6a799e6d9	0	0
1	offer received	10736	0	0b1e1539f2cc45b7b9fa7c272da2e1d7	0	0
2	offer received	15044	0	2906b810c7d4411798c6938adc9daaa5	0	0
3	offer received	9525	0	fafdcd668e3743c1bb461111dcafc2a4	0	0
4	offer received	6940	0	4d5c57ea9a6940dd891ad53e9dbe8da0	0	0

In [76]:
```
clean_transcript.event.unique()
```
Out[76]:
```
array(['offer received', 'offer viewed', 'transaction', 'offer completed'], d
type=object)
```

In [77]:
```
#we will focus on 'offer viewed' or 'offer completed' since we need to focus o
n customer who sow the 'offer viewed' and complated.
# tacking out all events of 'transaction' , 'offer received' from our clean_tr
anscript dataset
clean_transcript = clean_transcript[clean_transcript['event'] != 'transactio
n']
clean_transcript = clean_transcript[clean_transcript['event'] != 'offer receiv
ed']
```

In [78]:
```
clean_transcript['event'].unique()
```
Out[78]:
```
array(['offer viewed', 'offer completed'], dtype=object)
```

In [79]:
```
# replacing the 'event' categorical labels with coressponding numerical label
#key will be for 'offer completed' = 1 and  'offer viewed' = 2
labels_event = clean_transcript['event'].astype('category').cat.categories.tol
ist()
replace_map_comp_event = {'event' : {k: v for k,v in zip(labels_event,list(ran
ge(1,len(labels_event)+1)))}}
clean_transcript.replace(replace_map_comp_event, inplace=True)
```

In [80]:
```
clean_transcript.head()
```
Out[80]:

	event	customer_id	time	offer_id	amount	reward
12650	2	3729	0	f19421c1d4aa40978ebb69ca19b0e20d	0	0
12651	2	13995	0	5a8bc65990b245e5a138643cd4eb9837	0	0
12652	2	1052	0	4d5c57ea9a6940dd891ad53e9dbe8da0	0	0
12653	2	170	0	ae264e3637204a6fb9bb56bc8210ddfd	0	0
12655	2	12744	0	5a8bc65990b245e5a138643cd4eb9837	0	0

In [81]:
```
clean_transcript.replace(replace_map_comp_offer_id, inplace=True)#replacing of
fer_id with numeric value
clean_transcript.head()
```
Out[81]:

	event	customer_id	time	offer_id	amount	reward
12650	2	3729	0	9	0	0
12651	2	13995	0	6	0	0
12652	2	1052	0	5	0	0
12653	2	170	0	8	0	0
12655	2	12744	0	6	0	0

Merging the three clean datasets into master table

In [82]:
```
master_df = pd.merge(clean_transcript,clean_portfolio,how='left',on='offer_i
d')#will merge 'transcript' with 'portfolio' on 'offer_id'
```

In [83]:
```
master_df = pd.merge(master_df,clean_profile,how='left',on='customer_id')#will
merge our master table  with 'profile' on 'customer_id'
```

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

Out[84]:

	event	customer_id	time	offer_id	amount	reward_x	difficulty	duration_h	offer_type	rewar
0	2	3729	0	9	0	0	0.25	120	1	
1	2	13995	0	6	0	0	0.00	72	3	
2	2	1052	0	5	0	0	0.50	120	1	
3	2	170	0	8	0	0	0.50	168	1	
4	2	12744	0	6	0	0	0.00	72	3	

In [85]:
```
master_df.isnull().sum() #checking id there is any Nun values in our clean mas
ter table
```

Out[85]:
```
event                  0
customer_id            0
time                   0
offer_id               0
amount                 0
reward_x               0
difficulty             0
duration_h             0
offer_type             0
reward_y               0
channel_email          0
channel_mobile         0
channel_social         0
channel_web            0
gender              9000
age_group           9000
income_range        9000
member_type        32544
membership_year     9000
dtype: int64
```

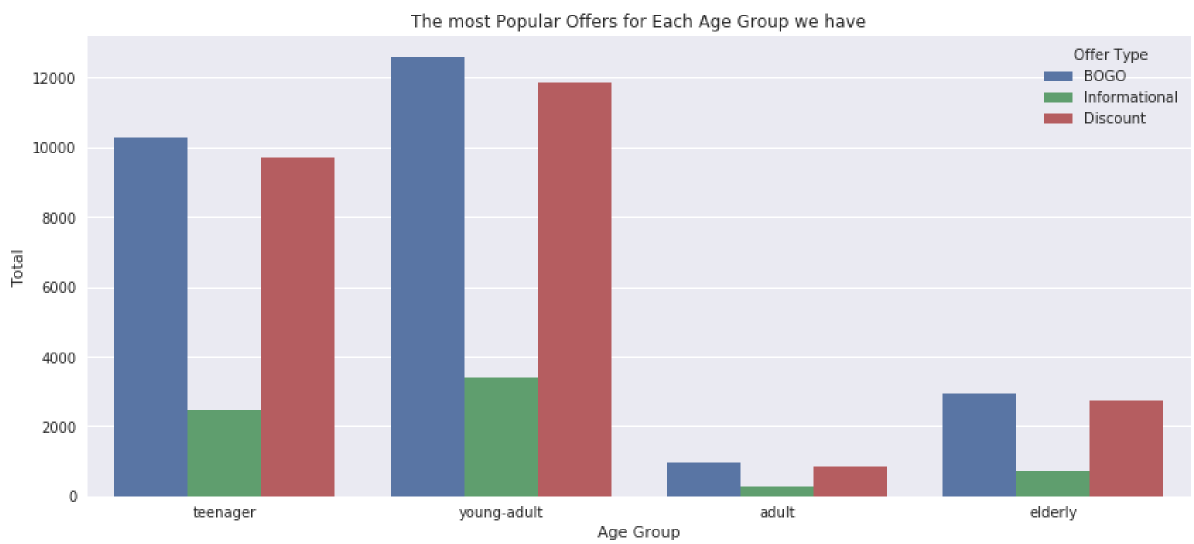
In [86]:
```
master_df = master_df.dropna(how='any',axis=0) #removing any Nun val from the
dataset
```

Let do some analyisi on our master table

- what is the populer offers for each age group we have
- Count of new member per each yeat starbucks has
- Popular Offers according to Gender
- Finding form all 'offer viewed' how many 'complete'
- based on demographic data will find the highest income range based on gender

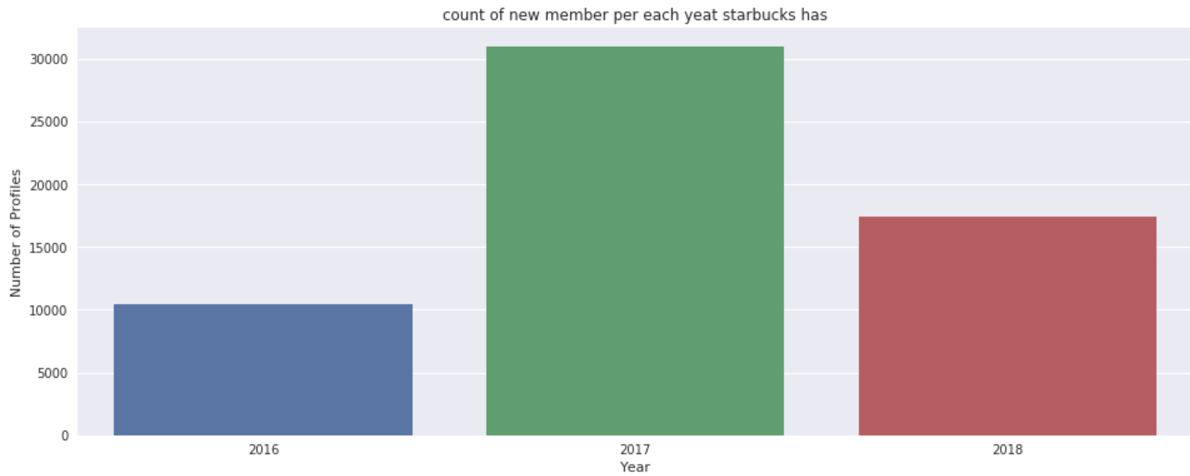
In [87]:
```
# Before begin we need to map the key for each categories to have them on our figure as legend .
master_df['event'] = master_df['event'].map({1: 'Completed', 2: 'Viewed'})
master_df['offer_type'] = master_df['offer_type'].map({1: 'BOGO', 2: 'Discount', 3: 'Informational'})
master_df['income_range'] = master_df['income_range'].map({1: 'Average', 2: 'Above-Average', 3:'High'})
master_df['age_group'] = master_df['age_group'].map({1: 'teenager', 2: 'young-adult', 3:'adult', 4:'elderly'})
```

In [88]:
```
plt.figure(figsize=(14, 6))
g = sns.countplot(x="age_group", hue="offer_type", data=master_df)
plt.title('The most Popular Offers for Each Age Group we have')
plt.ylabel('Total')
plt.xlabel('Age Group')
xlabels = ['teenager','young-adult','adult','elderly']
g.set_xticklabels(xlabels)
plt.xticks(rotation = 0)
plt.legend(title='Offer Type')
plt.show();
```

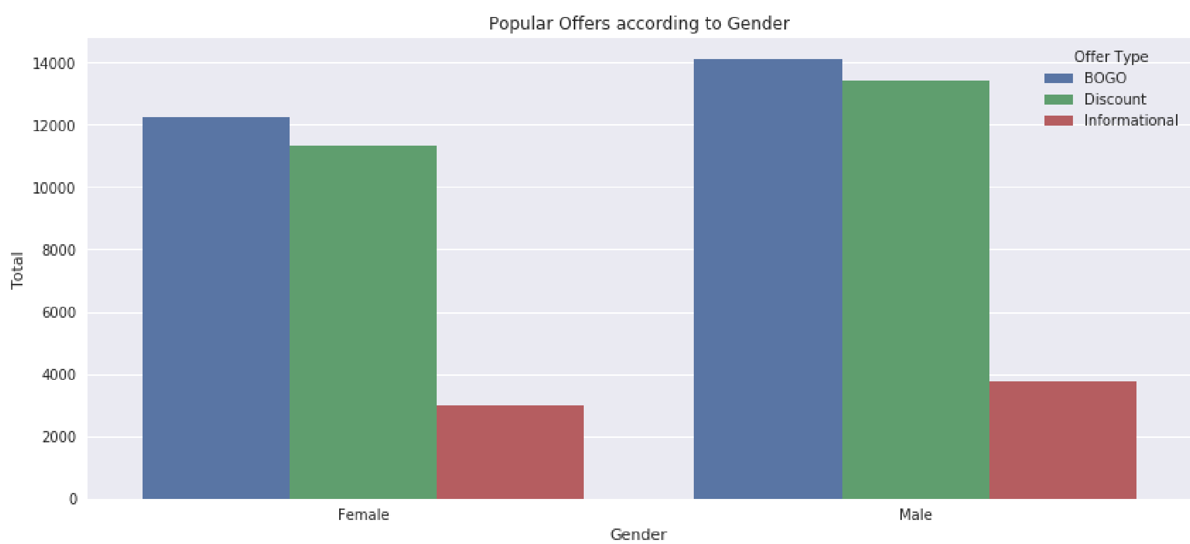


In [89]:
```
master_df['membership_year'] = master_df['membership_year'].astype(int)
```

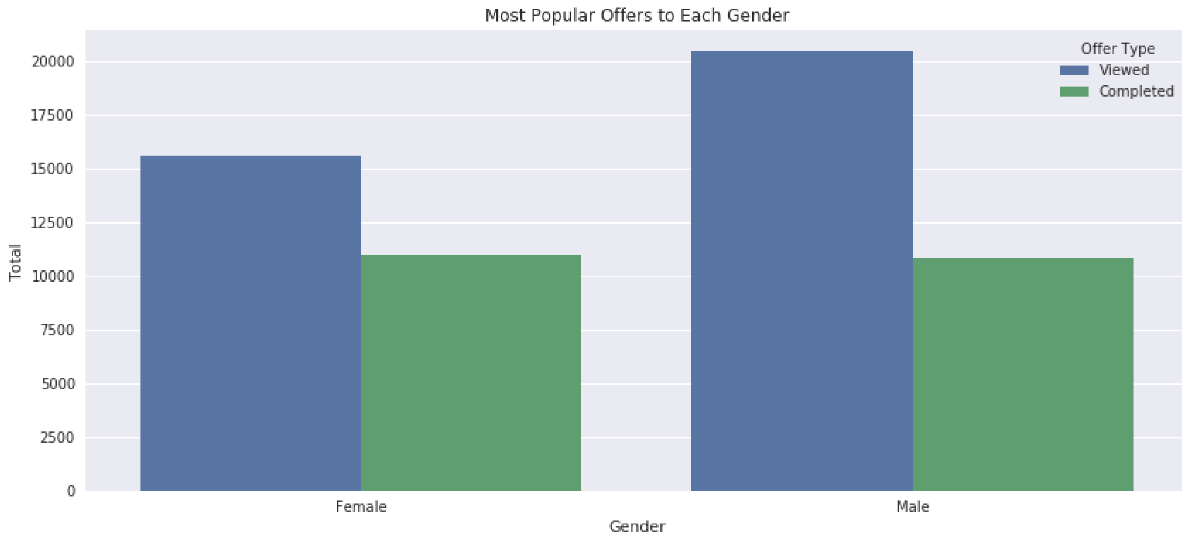
In [90]:
```
plt.figure(figsize=(16, 6))
sns.countplot(master_df['membership_year'])
plt.title('count of new member per each yeat starbucks has')
plt.ylabel('Number of Profiles')
plt.xlabel('Year')
plt.xticks()
plt.show();
```



In [91]:
```
plt.figure(figsize=(14, 6))
g = sns.countplot(x='gender', hue="offer_type", data= master_df[master_df["gen
der"] != 3])
plt.title('Popular Offers according to Gender')
plt.ylabel('Total')
plt.xlabel('Gender')
xlabels = ['Female', 'Male']
g.set_xticklabels(xlabels)
plt.legend(title='Offer Type')
plt.show();
```



In [92]:
```
plt.figure(figsize=(14, 6))
g = sns.countplot(x='gender', hue="event", data= master_df[master_df["gender"]
!= 3])
plt.title('Most Popular Offers to Each Gender')
plt.ylabel('Total')
plt.xlabel('Gender')
xlabels = ['Female', 'Male']
g.set_xticklabels(xlabels)
plt.legend(title='Offer Type')
plt.show();
```



In [93]:
```
#Finding form all 'offer viewed' how many 'complete'
total_trans_g_o = master_df[master_df["gender"] != 3].groupby(['gender','offer
_type']).count()
total_trans_g_e = master_df[master_df["gender"] != 3].groupby(['gender','even
t']).count()
total_trans_go_o_t = total_trans_g_o.loc[(1)]['event'].sum()
total_trans_go_o_tt = total_trans_g_o.loc[(2)]['event'].sum()
total_trans_go_o_t_offers_f = total_trans_g_o.loc[(1)].loc[['BOGO', 'Discoun
t', 'Informational']]['event'].sum()
total_trans_go_o_t_offers_m = total_trans_g_o.loc[(2)].loc[['BOGO', 'Discoun
t', 'Informational']]['event'].sum()
```

In [94]:
```
print('Finding form all offer viewed how many complete')
print('For Males:')
print(f"Number of offer viewed: {total_trans_g_e.loc[(2, 'Viewed')].values
[0]}.")
print(f"Number of offer completed: {total_trans_g_e.loc[(2, 'Completed')].valu
es[0]}, {round((total_trans_g_e.loc[(2, 'Completed')].values[0]/total_trans_g_
e.loc[(2, 'Viewed')].values[0])*100,2)}% of total offers viewed.")
print('For Females:')
print(f"Number of offer viewed: {total_trans_g_e.loc[(1, 'Viewed')].values
[0]}.")
print(f"Number of offer completed: {total_trans_g_e.loc[(1, 'Completed')].valu
es[0]}, {round((total_trans_g_e.loc[(1, 'Completed')].values[0]/total_trans_g_
e.loc[(1, 'Viewed')].values[0])*100,2)}% of total offers viewed.")
print("\n")
```

```
Finding form all offer viewed how many complete
For Males:
Number of offer viewed: 20432.
Number of offer completed: 10833, 53.02% of total offers viewed.
For Females:
Number of offer viewed: 15569.
Number of offer completed: 10979, 70.52% of total offers viewed.
```

In [95]:
```
plt.figure(figsize=(14, 6))
g = sns.countplot(x="gender", hue="income_range", data= master_df[master_df["g
ender"] != 3])
plt.title('Income Range per Gender')
plt.ylabel('Income Range')
xlabels = ['Female', 'Male']
g.set_xticklabels(xlabels)
plt.xlabel('Gender')
plt.xticks(rotation = 0)
plt.show();
```

In [96]:
```
# We need to replace the categorical values to numerical values before we comp
lete
labels_event1 = master_df['event'].astype('category').cat.categories.tolist()
replace_map_comp_event1 = {'event' : {k: v for k,v in zip(labels_event1,list(r
ange(1,len(labels_event1)+1)))}}

labels_income1 = master_df['income_range'].astype('category').cat.categories.t
olist()
replace_map_comp_income_range1 = {'income_range' : {k: v for k,v in zip(labels
_income1,list(range(1,len(labels_income1)+1)))}}

labels_offer_type1 = master_df['offer_type'].astype('category').cat.categorie
s.tolist()
replace_map_comp_offer_type1 = {'offer_type' : {k: v for k,v in zip(labels_off
er_type1,list(range(1,len(labels_offer_type1)+1)))}}

master_df.replace(replace_map_comp_event1, inplace=True)
master_df.replace(replace_map_comp_offer_type1, inplace=True)
master_df.replace(replace_map_comp_income_range1, inplace=True)
master_df.replace(replace_map_comp_age_group, inplace=True)
```

In [97]:
```
master_df.head()
```

Out[97]:

	event	customer_id	time	offer_id	amount	reward_x	difficulty	duration_h	offer_type	rewar
0	2	3729	0	9	0	0	0.25	120	1	
1	2	13995	0	6	0	0	0.00	72	3	
2	2	1052	0	5	0	0	0.50	120	1	
3	2	170	0	8	0	0	0.50	168	1	
7	2	9372	0	2	0	0	0.35	168	2	

Data Modeling

We will build a model that can predict how the customer respond to offers

Will need target the columns :

- Event columns that countain ('offer completed','offer viewed')

In [98]:
```
#but First we need to change the reward_x columns name into reward
master_df.rename(columns ={'reward_x':'reward'}, inplace = True)
```

In [99]:
```
master_df.columns
```

Out[99]:
```
Index(['event', 'customer_id', 'time', 'offer_id', 'amount', 'reward',
       'difficulty', 'duration_h', 'offer_type', 'reward_y', 'channel_email',
       'channel_mobile', 'channel_social', 'channel_web', 'gender',
       'age_group', 'income_range', 'member_type', 'membership_year'],
      dtype='object')
```

In [100]:
```
# Split the data into features and target label
X = master_df[['offer_id','amount','reward','difficulty','duration_h','offer_t
ype','gender','age_group','income_range', 'member_type']]
Y = master_df['event']
```

In [101]:
```
scaler = MinMaxScaler()
features = ['amount', 'reward', 'duration_h']
X_scaled = X.copy()
X_scaled[features] = scaler.fit_transform(X_scaled[features])
X_scaled.head()
```

Out[101]:

	offer_id	amount	reward	difficulty	duration_h	offer_type	gender	age_group	income_range
0	9	0.0	0.0	0.25	0.285714	1	2.0	4	2
1	6	0.0	0.0	0.00	0.000000	3	3.0	3	2
2	5	0.0	0.0	0.50	0.285714	1	1.0	4	2
3	8	0.0	0.0	0.50	0.571429	1	1.0	1	2
7	2	0.0	0.0	0.35	0.571429	2	1.0	3	1

In [102]:
```
# creating training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, Y, random_state=42)
```

In [103]:
```
#will make a measurment for the accuracy for model
def predict_acc_score(model):
    pred = model.predict(X_test)

    # Calculate the absolute errors
    errors = abs(pred - y_test)

    # Calculate mean absolute percentage error
    mean_APE = 100 * (errors / y_test)
    accuracy = 100 - np.mean(mean_APE)

    return round(accuracy, 4)
```

In [104]:
```
#Decision Tree model

dectre = DecisionTreeClassifier()

dectre.fit(X_train, y_train)
print(f'Accuracy for Decision Tree classifier on training set: {round(dectre.s
core(X_train, y_train)*100,2)}%.')
print(f'Prediction Accuracy: {predict_acc_score(dectre)}%')
```

```
Accuracy for Decision Tree classifier on training set: 100.0%.
Prediction Accuracy: 100.0%
```

In [105]:
```
# Naive Bayes modle
NivBas = GaussianNB()
NivBas.fit(X_train, y_train)
print(f'Accuracy of SVM classifier on training set: {round(NivBas.score(X_trai
n, y_train)*100,2)}%.')
print(f'Prediction Accuracy: {predict_acc_score(NivBas)}%')
```

```
Accuracy of SVM classifier on training set: 100.0%.
Prediction Accuracy: 100.0%
```

Model Evaluation

In [108]:
```
# creating the variables that will be used to fill the results table
models = [dectre,NivBas]
model_names = [type(n).__name__ for n in models]
training_accuracy = [x.score(X_train, y_train)*100 for x in models]
predection_accuracy = [predict_acc_score(y) for y in models]
```

In [109]:
```
# structuring a table to view the results of the different model tried above
results = [training_accuracy, predection_accuracy]
results_df = pd.DataFrame(results, columns = model_names, index=['Training Acc
uracy', 'Predicting Accuracy'])
```

In [110]:
```
results_df
```

Out[110]:

	DecisionTreeClassifier	GaussianNB
Training Accuracy	100.0	100.0
Predicting Accuracy	100.0	100.0

Observation :

We can see from the function result that our model affter being fitting is score 100% of trainning and testing for each one of them

Conclusion :

- I found this project challenging, mainly due to the structure of the data in the transcript dataset.
- I have explored each dataset, visualize it to get an overall understanding on the data
- Preprocessing Data was the task that took most of the time and effort
- The dataset is a bit tricky required me to use my wrangling/ engineering and preprocessing skills
- I have created two types of model to make sure of result and compare

In [106]:
```
!!jupyter nbconvert *.ipynb
```

Out[106]:
```
['[NbConvertApp] Converting notebook Starbucks_Capstone_notebook.ipynb to htm
l',
 '[NbConvertApp] Writing 492062 bytes to Starbucks_Capstone_notebook.html',
 '[NbConvertApp] Converting notebook Starbucks_Capstone_notebook-zh.ipynb to
html',
 '[NbConvertApp] Writing 279110 bytes to Starbucks_Capstone_notebook-zh.htm
l']
```

In [ ]: