Starbucks Capstone Challenge

1. Introduction

Project Overview

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.

Problem Statement

The purpose of this project is to aggregate transaction, demographic, and offer data to see which demographic groups respond best to different types of offers. Because the underlying simulator only contains one product, although Starbucks sells hundreds, this data set is a simplified version of the real Starbucks app.

Metrics

Because the goal of the project is to create a classification model, I chose accuracy and F1 score as model evaluation metrics.

The reason I chose both metrics is that when the dataset is imbalanced, accuracy alone cannot objectively show how the model is performing on the dataset, whereas F1 score provides a better sense of model performance than accuracy alone because it accounts for both false positives and false negatives. When the class distribution is skewed, F1 may be more useful than accuracy.

Datasets

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

---

2. Explanatory Data Analysis

Load Packages

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

from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score, f1_score
from sklearn.metrics import fbeta_score, make_scorer
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
print('Done!')
```
```
Done!
```

Load Datasets

In [2]:
```
# 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)

# Have an idea of the datasets shapes
print(portfolio.shape)
print(profile.shape)
print(transcript.shape)
```
```
(10, 6)
(17000, 5)
(306534, 4)
```

In this section, I will examine the problem and prepare the necessary features. Investigating the datasets, which includes checking abnormalities or characteristics about the data, displaying the data distribution.

Portfolio: Data Exploration & Visualization

Explore Portfolio Dataset

- Check if the dataset has abnormalities (missing values, duplicates).
- Know more about the features' characteristics.
- Check the features' unique values
- Display the features distribution.

In [3]:
```
portfolio.head()
```

Out[3]:

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

In [4]:
```
# Checking if the dataset has abnormalities (missing values).
portfolio.isnull().sum()
```
Out[4]:
```
reward        0
channels      0
difficulty    0
duration      0
offer_type    0
id            0
dtype: int64
```

Luckily, there is no missing values in portfolio dataset.

In [5]:
```
# Checking if the dataset has abnormalities (duplicates).
portfolio.columns.duplicated().sum()
```
Out[5]:
```
0
```

Luckily, there is no duplicate values in portfolio dataset.

In [6]:
```
# Know more about the features' characteristics.
portfolio.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   reward      10 non-null     int64
 1   channels    10 non-null     object
 2   difficulty  10 non-null     int64
 3   duration    10 non-null     int64
 4   offer_type  10 non-null     object
 5   id          10 non-null     object
dtypes: int64(3), object(3)
memory usage: 608.0+ bytes
```

In the preprocceing section, I will convert these features (`channels` , `offer_type` , `id`) to the right data type.

In [7]:
```
# Checking the features' unique values
print(portfolio[['difficulty', 'duration', 'id', 'offer_type', 'reward']].nunique())
```
```
difficulty     5
duration       5
id            10
offer_type     3
reward         5
dtype: int64
```

In [8]:
```
portfolio.describe().T.style
```

Out[8]:

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

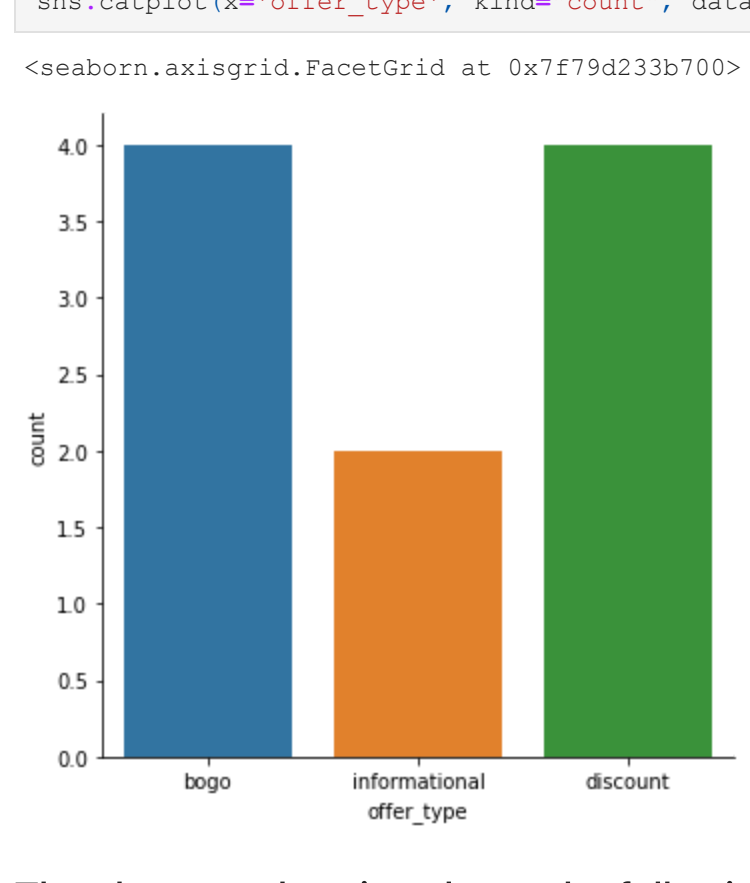
In [9]:
```
# Count of each data type
portfolio.dtypes.value_counts()
```
Out[9]:
```
int64     3
object    3
dtype: int64
```

In [10]:
```
# Handy list of all the string/text columns in the dataset
list(portfolio.select_dtypes(include=object))
```
Out[10]:
```
['channels', 'offer_type', 'id']
```

In [11]:
```
# Number of unique values in each column
print(portfolio[['difficulty', 'duration', 'id', 'offer_type', 'reward']].nunique())
```
```
difficulty     5
duration       5
id            10
offer_type     3
reward         5
dtype: int64
```

In [12]:
```
portfolio['offer_type'].unique()
```
Out[12]:
```
array(['bogo', 'informational', 'discount'], dtype=object)
```

In [13]:
```
sns.catplot(x='offer_type', kind="count", data=portfolio,)
```
Out[13]:
```
<seaborn.axisgrid.FacetGrid at 0x7f79d233b700>
```



The above exploration shows the following:

- The dataset has no missing values nor duplicates.
- There are three features that would require further work.
- There are 10 unique offers and three unique offer types ('bogo', 'informational' and 'discount').

Portfolio: Data Preprocessing

- Work on the data type for these features (`channels` , `offer_type` , `id`).
  - On hot encoding `channels` features
  - Convert the data type for these features (`offer_type` , `id`) to string.
  - Replace the categorical values to numrical for `offer_type` .
- Convert duration column unit to hours.
- Drop `channels` column.
- Show the cleaned dataset.

In [14]:
```
convert_dict = {'id': str,
                'offer_type': str
               }
```

In [15]:
```
# convert portfolio id and offer_type to string
portfolio = portfolio.astype(convert_dict)
```

In [16]:
```
# Change the unit of 'duration' column from days to hours
portfolio['duration'] = portfolio['duration']*24
```

In [17]:
```
# Rename id and duration columns
portfolio.rename({'id': 'offer_id','duration':'duration_h'}, axis=1, inplace= True)
```

In [18]:
```
# Apply one hot encoding to channels column
portfolio['web'] = portfolio['channels'].apply(lambda x: 1 if 'web' in x else 0)
portfolio['email'] = portfolio['channels'].apply(lambda x: 1 if 'email' in x else 0)
portfolio['mobile'] = portfolio['channels'].apply(lambda x: 1 if 'mobile' in x else 0)
portfolio['social'] = portfolio['channels'].apply(lambda x: 1 if 'social' in x else 0)
```

In [19]:
```
# Replace categorical variable to numeric in offer_type
portfolio['offer_type'].replace(['bogo', 'informational','discount'],
                                [0, 1,2], inplace=True)
```

In [20]:
```
# Drop channels column
portfolio.drop(['channels'], axis=1, inplace=True)
```

In [21]:
```
# Cleaned Portfolio Dataset
portfolio.head()
```

Out[21]:

	reward	difficulty	duration_h	offer_type	offer_id	web	email	mobile
0	10	10	168	0	ae264e3637204a6fb9bb56bc8210ddfd	0	1	1
1	10	10	120	0	4d5c57ea9a6940dd891ad53e9dbe8da0	1	1	1
2	0	0	96	1	3f207df678b143eea3cee63160fa8bed	1	1	1
3	5	5	168	0	9b98b8c7a33c4b65b9aebfe6a799e6d9	1	1	1
4	5	20	240	2	0b1e1539f2cc45b7b9fa7c272da2e1d7	1	1	0

Profile: Data Exploration & Visualization

Explore Profile Dataset

- Check if the dataset has abnormalities (missing values, duplicates).
- Know more about the features' characteristics.
- Check the features' unique values
- Display the features distribution.

In [22]:
```
profile.head()
```

Out[22]:

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

In [23]:
```
# Checking if the dataset has abnormalities (missing values).
profile.isnull().sum()
```
Out[23]:
```
gender              2175
age                    0
id                     0
became_member_on       0
income              2175
dtype: int64
```

There are missing values in profile dataset that need to be investigated.

In [24]:
```
# Checking if the dataset has abnormalities (duplicates).
portfolio.columns.duplicated().sum()
```
Out[24]:
```
0
```

Luckily, there is no duplicate values in portfolio dataset.

In [25]:
```
profile.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17000 entries, 0 to 16999
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   gender            14825 non-null  object
 1   age               17000 non-null  int64
 2   id                17000 non-null  object
 3   became_member_on  17000 non-null  int64
 4   income            14825 non-null  float64
dtypes: float64(1), int64(2), object(2)
memory usage: 664.2+ KB
```

In the preprocceing section, I will convert these features (`gender` , `became_member_on` , `id`) to the right format.

In [26]:
```
profile.dtypes.value_counts()
```
Out[26]:
```
object     2
int64      2
float64    1
dtype: int64
```

In [27]:
```
profile.describe().T.style
```

Out[27]:

	count	mean	std	min	25%
age	17000.000000	62.531412	26.738580	18.000000	45.000000
became_member_on	17000.000000	20167034.234118	11677.499961	20130729.000000	20160526.000000
income	14825.000000	65404.991568	21598.299410	30000.000000	49000.000000

Here we can see that the max values for an age column is 118!

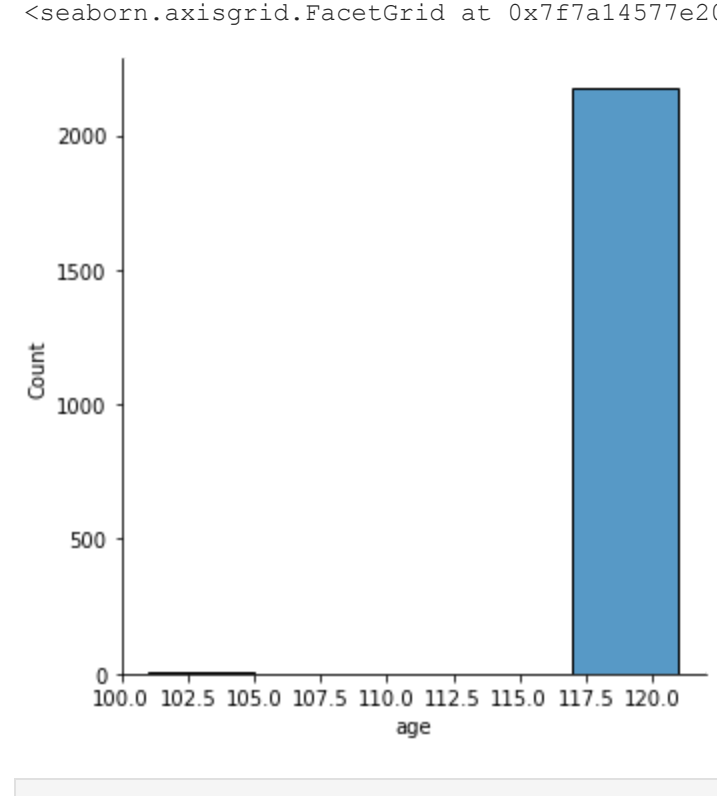
In [28]:
```
# Checking 118 age's records
profile[profile['age']==118]
```

Out[28]:

	gender	age	id	became_member_on	income
0	None	118	68be06ca386d4c31939f3a4f0e3dd783	20170212	NaN
2	None	118	38fe809add3b4fcf9315a9694bb96ff5	20180712	NaN
4	None	118	a03223e636434f42ac4c3df47e8bac43	20170804	NaN
6	None	118	8ec6ce2a7e7949b1bf142def7d0e0586	20170925	NaN
7	None	118	68617ca6246f4fbc85e91a2a49552598	20171002	NaN
...	...	...	...	...	...
16980	None	118	5c686d09ca4d475a8f750f2ba07e0440	20160901	NaN
16982	None	118	d9ca82f550ac4ee58b6299cf1e5c824a	20160415	NaN
16989	None	118	ca45ee1883624304bac1e4c8a114f045	20180305	NaN
16991	None	118	a9a20fa8b5504360beb4e7c8712f8306	20160116	NaN
16994	None	118	c02b10e8752c4d8e9b73f918558531f7	20151211	NaN

2175 rows × 5 columns

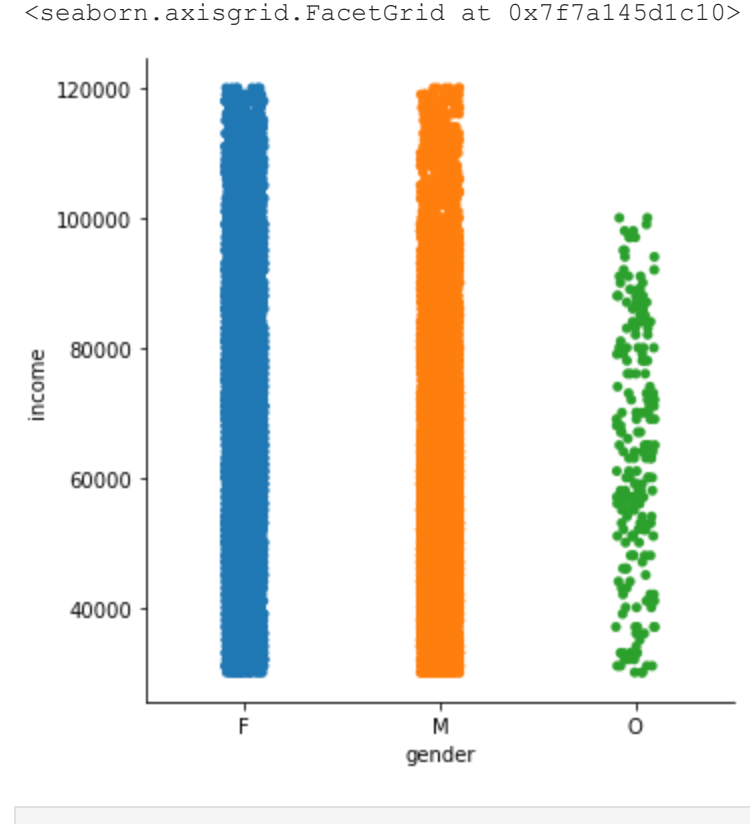
In [29]:
```
sns.displot(profile, x=profile[profile["age"]>100]['age'], binwidth=4)
```
Out[29]:
```
<seaborn.axisgrid.FacetGrid at 0x7f7a14577e20>
```



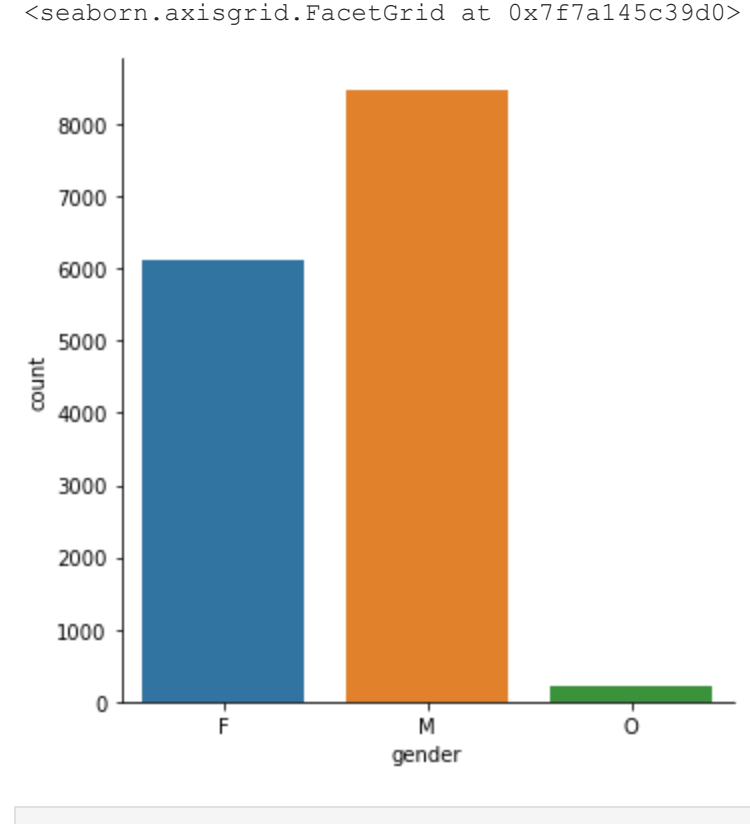
In [30]:
```
profile.where(profile['age']==118).count()
```
Out[30]:
```
gender                 0
age                 2175
id                  2175
became_member_on    2175
income                 0
dtype: int64
```

All the missing values are associated with 118 age's records, for that I will drop each record with 118 age value in the preprocceing section

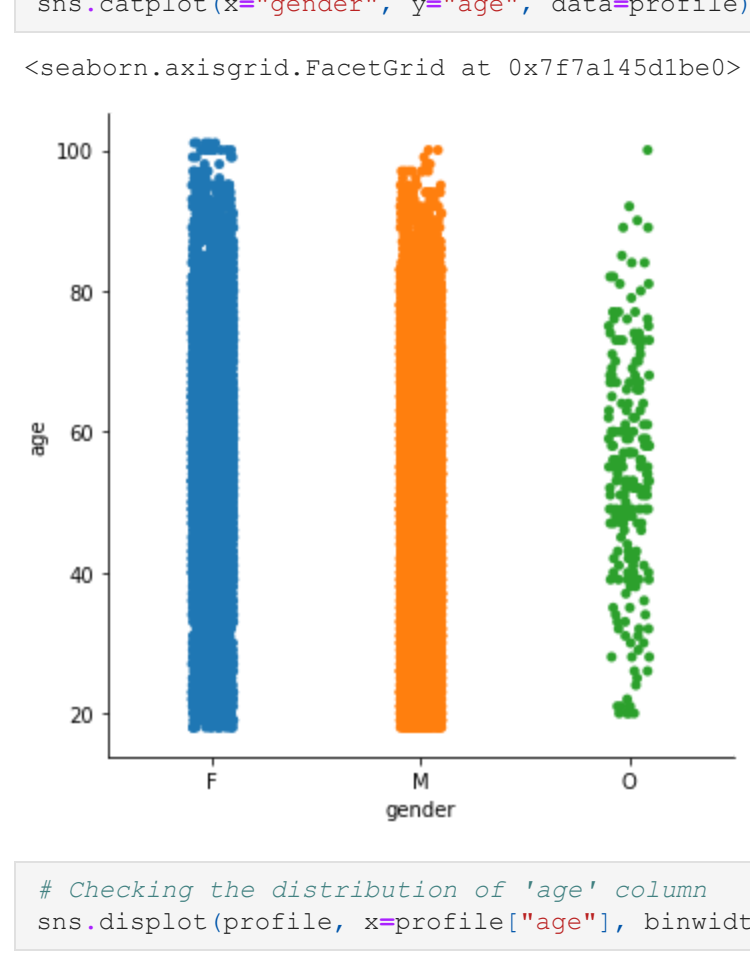
In [31]:
```
sns.catplot(x='gender', y='income',data=profile)
```
Out[31]:
```
<seaborn.axisgrid.FacetGrid at 0x7f7a145d1c10>
```



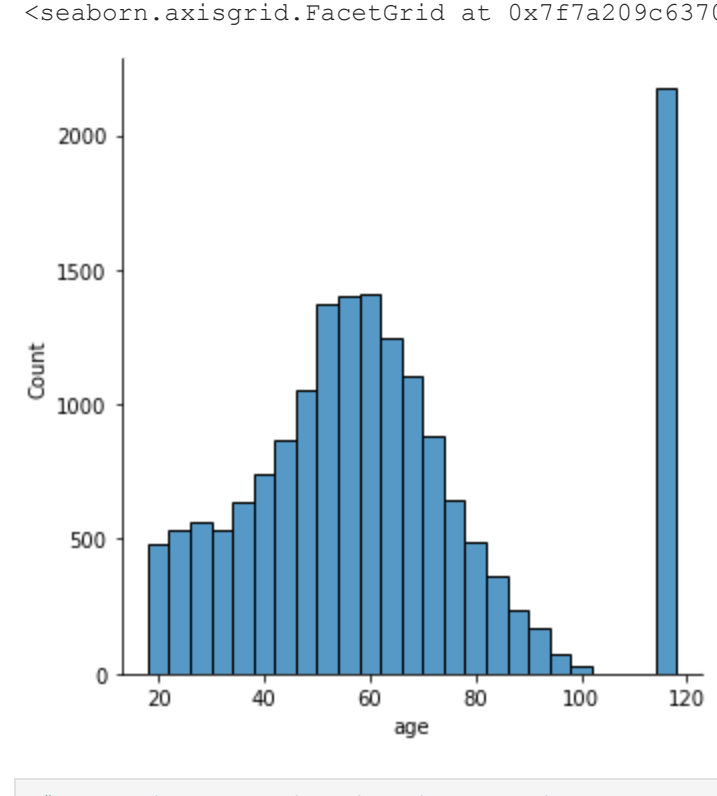
In [32]:
```
sns.catplot(x='gender', kind="count", data=profile)
```
Out[32]:
```
<seaborn.axisgrid.FacetGrid at 0x7f7a145c39d0>
```



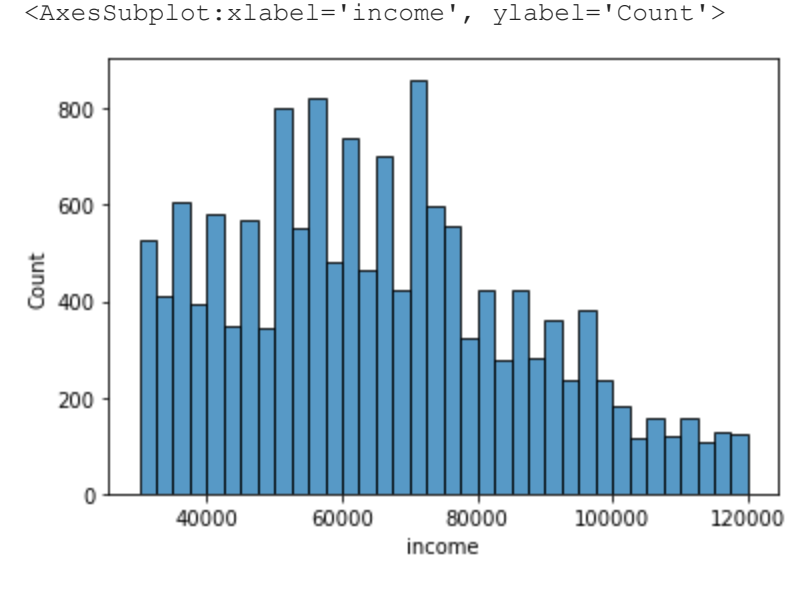
In [33]:
```
sns.catplot(x="gender", y="age", data=profile)
```
Out[33]:
```
<seaborn.axisgrid.FacetGrid at 0x7f7a145d1be0>
```



In [34]:
```
# Checking the distribution of 'age' column
sns.displot(profile, x=profile["age"], binwidth=4)
```
Out[34]:
```
<seaborn.axisgrid.FacetGrid at 0x7f7a209c6370>
```



In [35]:
```
# Checking the distribution of 'income' column
sns.histplot(profile, x=profile["income"])
```
Out[35]:
```
<AxesSubplot:xlabel='income', ylabel='Count'>
```



The above exploration shows the following:

- The dataset has 2175 missing values and no duplicates.
- The distribution of `age` shows the follwoing:
  - The range of Starbuck customer age is (18 - 101).
  - The most customer age range is (45 - 65).
- The distribution of `income` shows the follwoing:
  - The range of Starbuck customer income is (30K - 120K).
  - The most custimer income range is (50K - 75K).
- There are three features that would require further work.
- All the missing values related to one age value.

Profile: Data Preprocessing

- Work on the data type for these features (`gender` , `became_member_on` , `id`).
  - Rename `id` column to customer_id.
  - Replace `gender` categorical variable to numeric.
  - Change `became_member_on` format to the right one (YYYY-MM-DD).
- Drop all rows with 118 `age` value.
- Show the cleaned dataset.

In [36]:
```
# Drop all rows with 118 age
profile.drop(profile[profile['age'] == 118].index, inplace = True)
```

In [37]:
```
# Rename id column to customer_id
profile.rename({'id': 'customer_id'}, axis=1, inplace= True)
```

In [38]:
```
# Change became_member_on type to the right one
profile['became_member_on'] = profile['became_member_on'].astype(str).astype('datetime
```

In [39]:
```
# Replace categorical variable to numeric in gender
profile['gender'].replace(['O', 'M','F'],
                          [0, 1,2], inplace=True)
```

In [40]:
```
# Cleaned Profile Dataset
profile.head()
```

Out[40]:

	gender	age	customer_id	became_member_on	income
1	2	55	0610b486422d4921ae7d2bf64640c50b	2017-07-15	112000.0
3	2	75	78afa995795e4d85b5d9ceeca43f5fef	2017-05-09	100000.0
5	1	68	e2127556f4f64592b11af22de27a7932	2018-04-26	70000.0
8	1	65	389bc3fa690240e798340f5a15918d5c	2018-02-09	53000.0
12	1	58	2eeac8d8feae4a8cad5a6af0499a211d	2017-11-11	51000.0

Transcript: Data Exploration & Visualization

- Check if the dataset has abnormalities (missing values, duplicates).
- Know more about the features' characteristics.
- Check the features' unique values
- Display the features distribution.

Explore Transcript Dataset

In [41]:
```
transcript.head()
```

Out[41]:

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

In the preprocessing section, I will work on value since its values is dict.

In [42]:
```
# Checking if the dataset has abnormalities (missing values).
transcript.isnull().sum()
```
Out[42]:
```
person    0
event     0
value     0
time      0
dtype: int64
```

Luckily, there is no missing values in transcript dataset.

In [43]:
```
# Checking if the dataset has abnormalities (duplicates).
transcript.columns.duplicated().sum()
```
Out[43]:
```
0
```

Luckily, there is no duplicates in transcript dataset.

In [44]:
```
# Number of unique values in each column
print(transcript[['event', 'person', 'time']].nunique())
```
```
event         4
person    17000
time        120
dtype: int64
```

In [45]:
```
transcript.dtypes.value_counts()
```
Out[45]:
```
object    3
int64     1
dtype: int64
```

In [46]:
```
transcript.describe().T.style
```

Out[46]:

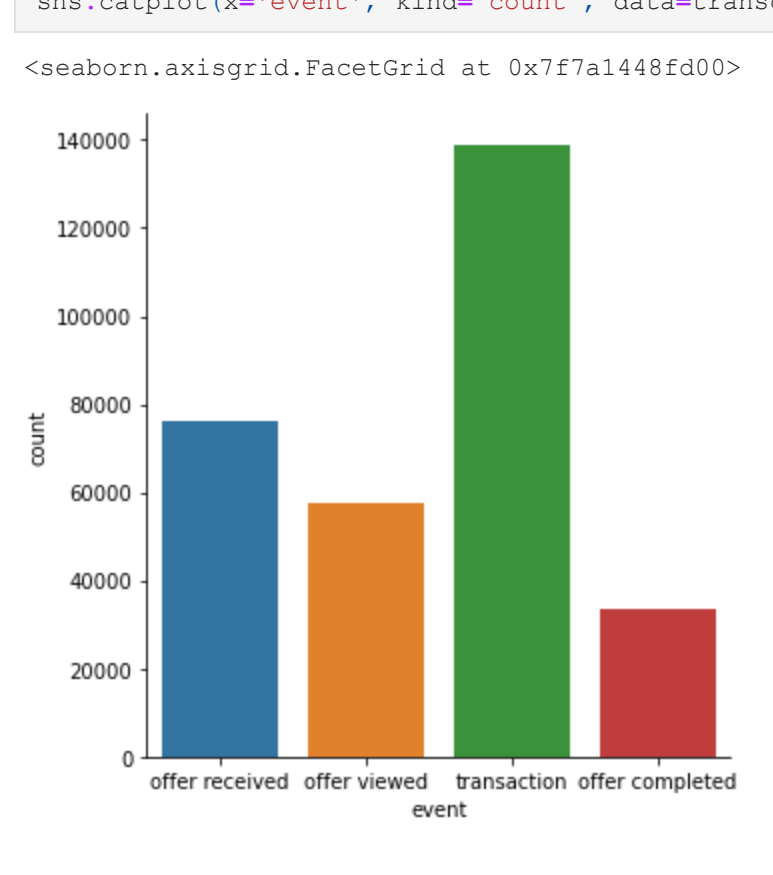
	count	mean	std	min	25%	50%	75%	r
time	306534.000000	366.382940	200.326314	0.000000	186.000000	408.000000	528.000000	714.000

In [47]:
```
# Checking the count of each event type
transcript.event.value_counts()
```
Out[47]:
```
transaction        138953
offer received      76277
offer viewed        57725
offer completed     33579
Name: event, dtype: int64
```

In [48]:
```
transcript.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 306534 entries, 0 to 306533
Data columns (total 4 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   person  306534 non-null  object
 1   event   306534 non-null  object
 2   value   306534 non-null  object
 3   time    306534 non-null  int64
dtypes: int64(1), object(3)
memory usage: 9.4+ MB
```

In [49]:
```
for col in transcript[['event']]:
    print(col, "\n", transcript[col].value_counts(dropna=False), "\n")
```
```
event
 transaction        138953
offer received      76277
offer viewed        57725
offer completed     33579
Name: event, dtype: int64
```

In [50]:
```
sns.catplot(x='event', kind="count", data=transcript)
```
Out[50]:
```
<seaborn.axisgrid.FacetGrid at 0x7f7a1448fd00>
```



The above exploration shows the following:

- The dataset has no missing values nor duplicates.
- In the dataset we have 17000 unique costomers.
- There are four types of `events` (offer received, offer viewed, offer completed, transaction)

Transcript: Data Preprocessing

- Rename person column to customer_id
- Rename time column to time_h to represent the feature unit.
- Match the avilable customer in the profile dataset with the one in transcript.
- Extract `value` column values into different columns.
- Drop `value` column after the extraction.
- Drop transaction rows since I'm only interested in only (offer completed, offer viewed).
- One hot encoding `event` column.
- Show the cleaned dataset.

In [51]:
```
# Reanme person column
transcript.rename({'person': 'customer_id'}, axis=1, inplace= True)
```

In [52]:
```
# Remove customer id's that are not in the customer profile DataFrame
transcript = transcript[transcript['customer_id'].isin(profile['customer_id'])]
```

In [53]:
```
# Unpack the dict values so that each value will be represent in separate column
transcript = pd.concat([transcript, transcript['value'].apply(pd.Series)], axis=1)
```

In [54]:
```
# clean up the duplicates in offer id and offer_id and meger into one column
transcript['clean_id'] = np.where(transcript['offer id'].isnull() & transcript['offer_

# drop the original id columns
transcript.drop(['offer id', 'offer_id'], axis=1, inplace=True)

# rename the offer_id column
transcript.rename(columns={'clean_id': 'offer_id'}, inplace=True)
```

In [55]:
```
# drop value column
transcript.drop('value', axis=1, inplace=True)
```

In [56]:
```
# Drop offer recevied rows, since I'm only interested in offer viewed and completed
transcript.drop(transcript[transcript['event']=='offer received'].index, inplace=True,
```

In [57]:
```
# Drop transaction rows
transcript.drop(transcript[transcript['event']== 'transaction'].index,axis=0,inplace =
```

In [58]:
```
# One hot encoding to event column
transcript['event'] = transcript['event'].apply(lambda x: 0 if 'offer viewed' in x els
```

In [59]:
```
# Drop amount and reward columns since they have a huage number of missing valuse
transcript.drop('amount', axis=1, inplace=True)
transcript.drop('reward', axis=1, inplace=True)
```

In [60]:
```
transcript.rename({'time':'time_h'}, axis=1, inplace=True)
```

In [61]:
```
# Cleaned transcript Dataset
transcript.head()
```

Out[61]:

	customer_id	event	time_h	offer_id
12650	389bc3fa690240e798340f5a15918d5c	0	0	f19421c1d4aa40978ebb69ca19b0e20d

12651	d1ede868e29245ea91818a903fec04c6	0	0	5a8bc65990b245e5a138643cd4eb9837
12652	102e9454054946fda62242d2e176fdce	0	0	4d5c57ea9a6940dd891ad53e9dbe8da0
12653	02c083884c7d45b39cc68e1314fec56c	0	0	ae264e3637204a6fb9bb56bc8210ddfd
12655	be8a5d1981a2458d90b255ddc7e0d174	0	0	5a8bc65990b245e5a138643cd4eb9837

Merging the three cleaned datasets

In [62]:

```
portfolio.head()
```

Out[62]:

	reward	difficulty	duration_h	offer_type	offer_id	web	email	mobile
0	10	10	168	0	ae264e3637204a6fb9bb56bc8210ddfd	0	1	1
1	10	10	120	0	4d5c57ea9a6940dd891ad53e9dbe8da0	1	1	1
2	0	0	96	1	3f207df678b143eea3cee63160fa8bed	1	1	1
3	5	5	168	0	9b98b8c7a33c4b65b9aebfe6a799e6d9	1	1	1
4	5	20	240	2	0b1e1539f2cc45b7b9fa7c272da2e1d7	1	1	0

In [63]:

```
profile.head()
```

Out[63]:

	gender	age	customer_id	became_member_on	income
1	2	55	0610b486422d4921ae7d2bf64640c50b	2017-07-15	112000.0
3	2	75	78afa995795e4d85b5d9ceeca43f5fef	2017-05-09	100000.0
5	1	68	e2127556f4f64592b11af22de27a7932	2018-04-26	70000.0
8	1	65	389bc3fa690240e798340f5a15918d5c	2018-02-09	53000.0
12	1	58	2eeac8d8feae4a8cad5a6af0499a211d	2017-11-11	51000.0

In [64]:

```
transcript.head()
```

Out[64]:

	customer_id	event	time_h	offer_id
12650	389bc3fa690240e798340f5a15918d5c	0	0	f19421c1d4aa40978ebb69ca19b0e20d
12651	d1ede868e29245ea91818a903fec04c6	0	0	5a8bc65990b245e5a138643cd4eb9837
12652	102e9454054946fda62242d2e176fdce	0	0	4d5c57ea9a6940dd891ad53e9dbe8da0
12653	02c083884c7d45b39cc68e1314fec56c	0	0	ae264e3637204a6fb9bb56bc8210ddfd
12655	be8a5d1981a2458d90b255ddc7e0d174	0	0	5a8bc65990b245e5a138643cd4eb9837

In [65]:

```
# Merge the transcript and portfolio datasets
master_df = transcript.merge(portfolio,how='left',on='offer_id')
```

In [66]:

```
# Merge the master_df and profile datasets
master_df = master_df.merge(profile,how='left', on ='customer_id')
```

In [67]:

```
master_df.head()
```

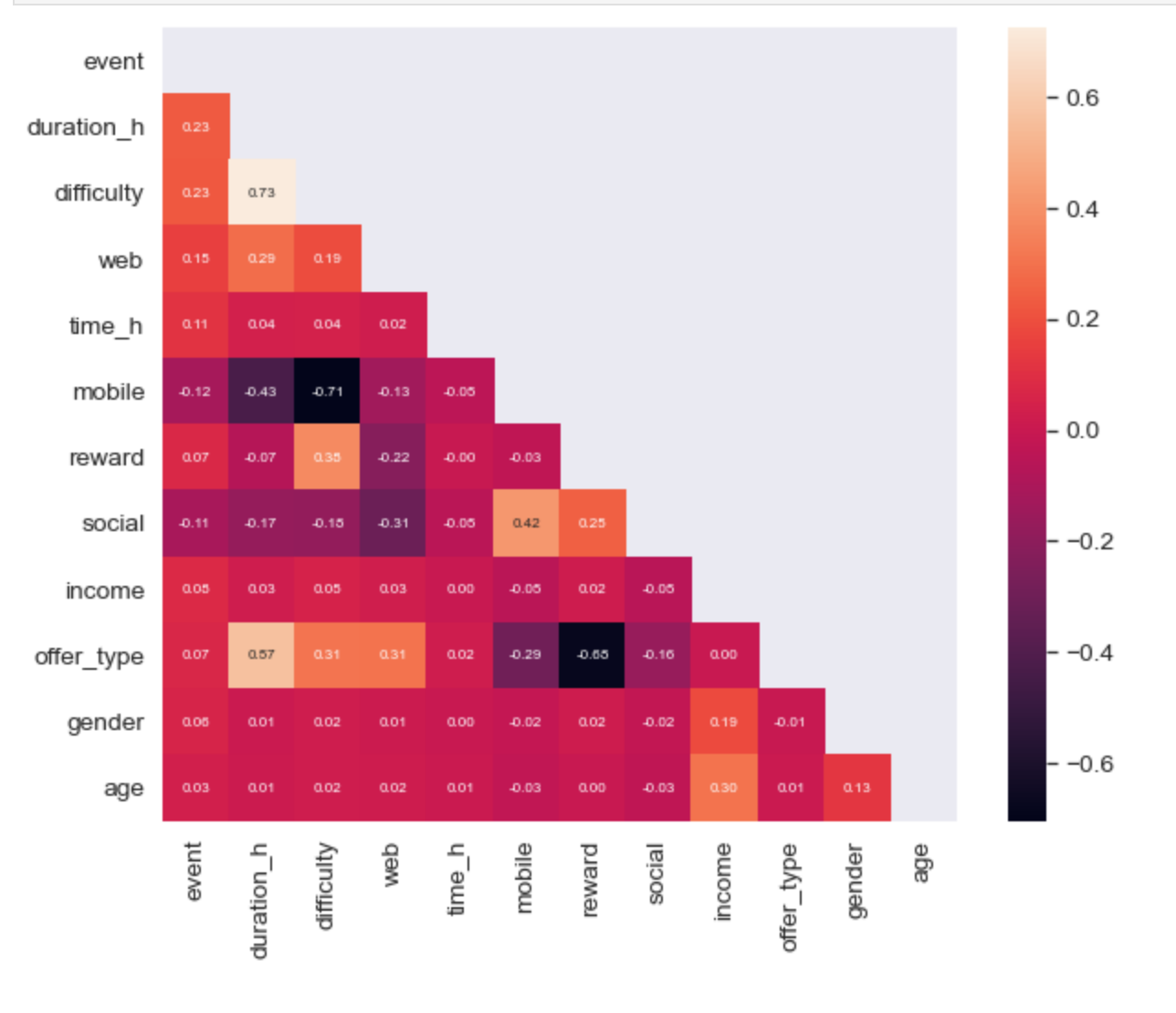
Out[67]:

	customer_id	event	time_h	offer_id	reward	di
0	389bc3fa690240e798340f5a15918d5c	0	0	f19421c1d4aa40978ebb69ca19b0e20d	5	
1	d1ede868e29245ea91818a903fec04c6	0	0	5a8bc65990b245e5a138643cd4eb9837	0	
2	102e9454054946fda62242d2e176fdce	0	0	4d5c57ea9a6940dd891ad53e9dbe8da0	10	
3	02c083884c7d45b39cc68e1314fec56c	0	0	ae264e3637204a6fb9bb56bc8210ddfd	10	
4	be8a5d1981a2458d90b255ddc7e0d174	0	0	5a8bc65990b245e5a138643cd4eb9837	0	

In [68]:

```
# Event correlation matrix
k = 17 #number of variables for heatmap
corrmat = abs(master_df.corr(method='spearman'))
# nlargest : Return this many descending sorted values
cols = corrmat.nlargest(k, 'event').index
cm = np.corrcoef(master_df[cols].values.T)
sns.set(font_scale=1.25)
f, ax = plt.subplots(figsize=(10, 8))

# Hide upper symmetric metrics
mask = np.zeros_like(cm)
mask[np.triu_indices_from(mask)] = True
sns.set_style("white")
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f',
                 annot_kws={'size': 8}, yticklabels=cols.values,
                 xticklabels=cols.values, mask = mask)
plt.show()
```



Part 3: Model Implementation & Evaluation

After I've finished preparing the data, I'll begin implementing models to determine which factors have the greatest impact on whether or not the client will respond to the offer.

As a result, I'll create models to forecast whether or not the consumer will respond to the offer using the 'event' feature as my target. I'll also select various models in order to obtain more results, which will assist me in obtaining a more accurate model.

Because the goal of the project is to create a classification model, I chose accuracy and F1 score as model evaluation metrics.

In [69]:

```
master_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 82304 entries, 0 to 82303
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customer_id       82304 non-null  object
 1   event             82304 non-null  int64
 2   time_h            82304 non-null  int64
 3   offer_id          82304 non-null  object
 4   reward            82304 non-null  int64
 5   difficulty        82304 non-null  int64
 6   duration_h        82304 non-null  int64
 7   offer_type        82304 non-null  int64
 8   web               82304 non-null  int64
 9   email             82304 non-null  int64
 10  mobile            82304 non-null  int64
 11  social            82304 non-null  int64
 12  gender            82304 non-null  int64
 13  age               82304 non-null  int64
 14  became_member_on  82304 non-null  datetime64[ns]
 15  income            82304 non-null  float64
dtypes: datetime64[ns](1), float64(1), int64(12), object(2)
memory usage: 10.7+ MB
```

In [70]:

```
master_df.columns
```

Out[70]:

```
Index(['customer_id', 'event', 'time_h', 'offer_id', 'reward', 'difficulty',
       'duration_h', 'offer_type', 'web', 'email', 'mobile', 'social',
       'gender', 'age', 'became_member_on', 'income'],
      dtype='object')
```

Split data into features and target labels, considering ONLY those features that I believe are important for my model to predict accurately.

Those features are as follows:

```
time_h
reward
difficulty
duration_h
offer_type
gender_F
gender_M
gender_O
age
income
```

Our target is:

```
'event' that will be either:
    1 : offer completed
    0 : offer viewed
```

In [71]:

```
# Selecting features and target values
X = master_df[['time_h','offer_type','difficulty','duration_h','gender','age','income
Y = master_df['event']
```

In [72]:

```
# Normalizing some numerical values
scaler = MinMaxScaler()
features = ['time_h','duration_h', 'difficulty']
X_scaled = X.copy()
X_scaled[features] = scaler.fit_transform(X_scaled[features])
X_scaled.head()
```

Out[72]:

	time_h	offer_type	difficulty	duration_h	gender	age	income
0	0.0	0	0.25	0.285714	1	65	53000.0
1	0.0	1	0.00	0.000000	0	53	52000.0
2	0.0	0	0.50	0.285714	2	69	57000.0
3	0.0	0	0.50	0.571429	2	20	30000.0
4	0.0	1	0.00	0.000000	1	39	51000.0

In [73]:

```
# Creating training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, Y, random_state=42)
```

In [74]:

```
#Decision Tree Model
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)
print(f'Accuracy of Decision Tree classifier on training set: {round(dt.score(X_train,
print(f'Testing Accuracy: {round((dt.score(X_test, y_test)*100),2)}%')

y_pred_dt = dt.predict(X_train)

DecisionTreeClassifier_predictor_accuracy = accuracy_score(y_train, y_pred_dt)
DecisionTreeClassifier_predictor_f1score = f1_score(y_train, y_pred_dt)

print("Decision Tree Classifier predictor accuracy: %.3f" % (DecisionTreeClassifier_p
print("Decision Tree Classifier predictor f1-score: %.3f" % (DecisionTreeClassifier_p
```

```
Accuracy of Decision Tree classifier on training set: 97.41%
Testing Accuracy: 59.27%
Decision Tree Classifier predictor accuracy: 0.974
Decision Tree Classifier predictor f1-score: 0.966
```

In [75]:

```
#Support Vector Machine Model

svm = SVC(gamma = 'auto')

svm.fit(X_train, y_train)
print(f'Accuracy of SVM classifier on training set: {round(svm.score(X_train, y_train)
print(f'Testing Accuracy: {round((svm.score(X_test, y_test)*100),2)}%')

y_pred_svm = svm.predict(X_train)

SVM_predictor_accuracy = accuracy_score(y_train, y_pred_svm)
SVM_predictor_f1score = f1_score(y_train, y_pred_svm)

print("Support Vector Machine predictor accuracy: %.3f" % (SVM_predictor_accuracy))
print("Support Vector Machine predictor f1-score: %.3f" % (SVM_predictor_f1score))
```

```
Accuracy of SVM classifier on training set: 96.49%
Testing Accuracy: 58.59%
Support Vector Machine predictor accuracy: 0.965
Support Vector Machine predictor f1-score: 0.953
```

In [76]:

```
#Naive Bayes Model

gnb = GaussianNB()

gnb.fit(X_train, y_train)
print(f'Accuracy of Naive Bayes on training set: {round(gnb.score(X_train, y_train)*10
print(f'Testing Accuracy: {round((gnb.score(X_test, y_test)*100),2)}%')

y_pred_gnb = gnb.predict(X_train)

NB_predictor_accuracy = accuracy_score(y_train, y_pred_gnb)
NB_predictor_f1score = f1_score(y_train, y_pred_gnb)

print("Naive Bayes predictor accuracy: %.3f" % (NB_predictor_accuracy))
print("Naive Bayes predictor f1-score: %.3f" % (NB_predictor_f1score))
```

```
Accuracy of Naive Bayes on training set: 61.54%
Testing Accuracy: 61.41%
Naive Bayes predictor accuracy: 0.615
Naive Bayes predictor f1-score: 0.476
```

In [77]:

```
#K-Nearest Neighbors Model

knn = KNeighborsClassifier()

knn.fit(X_train, y_train)
print(f'Accuracy of KNN classifier on training set: {round(knn.score(X_train, y_train)
print(f'Testing Accuracy: {round((knn.score(X_test, y_test)*100),2)}%')

y_pred_knn = knn.predict(X_train)

KNN_predictor_accuracy = accuracy_score(y_train, y_pred_knn)
KNN_predictor_f1score = f1_score(y_train, y_pred_knn)

print("KNeighbors Classifier predictor accuracy: %.3f" % (KNN_predictor_accuracy))
print("KNeighbors Classifier predictor f1-score: %.3f" % (KNN_predictor_f1score))
```

```
Accuracy of KNN classifier on training set: 74.68%
Testing Accuracy: 61.99%
KNeighbors Classifier predictor accuracy: 0.747
KNeighbors Classifier predictor f1-score: 0.657
```

In [78]:

```
#LogisticRegression Model
logreg = LogisticRegression()

logreg.fit(X_train, y_train)
print(f'Accuracy of Logistic regression classifier on training set: {round(logreg.sco
print(f'Testing Accuracy: {round((logreg.score(X_test, y_test)*100),2)}%')

y_pred_logreg = logreg.predict(X_train)

LogisticRegression_predictor_accuracy = accuracy_score(y_train, y_pred_logreg)
LogisticRegression_predictor_f1score = f1_score(y_train, y_pred_logreg)

print("Logistic Regression Classifier predictor accuracy: %.3f" % (LogisticRegression_
print("Logistic Regression Classifier predictor f1-score: %.3f" % (LogisticRegression_
```

```
Accuracy of Logistic regression classifier on training set: 59.33%
Testing Accuracy: 59.33%
Logistic Regression Classifier predictor accuracy: 0.593
Logistic Regression Classifier predictor f1-score: 0.273
```

We can observe from the results that Decision Tree's F1 performs somewhat better than the remining models.

However, the models' overall higher accuracy compared to the F1 score implies that it is better at predicting positive situations than negative cases, which is to be expected given the unbalanced classifications.

Hyperparameter Tuning

In this section I will use the GridSearch method to fine-tune the parameters of the initial model in order to improve performance.

In [79]:

```
tree_param = [{'criterion': ['entropy', 'gini'],
               'max_depth': [4,5,6,7,8,9,10,11,12,15,20,30,40,50,70,90,120,150]}]

grid_search = GridSearchCV(DecisionTreeClassifier(),tree_param, cv=5)
grid_search.fit(X_train, y_train)
grid_search.best_params_
```

Out[79]:

```
{'criterion': 'entropy', 'max_depth': 15}
```

In [80]:

```
#Decision Tree Model

dt = DecisionTreeClassifier(criterion= 'entropy', max_depth= 15)
dt.fit(X_train, y_train)
print(f'Accuracy of Decision Tree classifier on training set: {round(dt.score(X_train,
print(f'Testing Accuracy: {round((dt.score(X_test, y_test)*100),2)}%')

y_pred_dt = dt.predict(X_train)

DecisionTreeClassifier_predictor_accuracy = accuracy_score(y_train, y_pred_dt)
DecisionTreeClassifier_predictor_f1score = f1_score(y_train, y_pred_dt)

print("Decision Tree Classifier predictor accuracy: %.3f" % (DecisionTreeClassifier_p
print("Decision Tree Classifier predictor f1-score: %.3f" % (DecisionTreeClassifier_p
```

```
Accuracy of Decision Tree classifier on training set: 72.57%
Testing Accuracy: 67.46%
Decision Tree Classifier predictor accuracy: 0.726
Decision Tree Classifier predictor f1-score: 0.621
```

The model's result improved dramatically after using gridSerach.

Part 4: API_Packaging

This part is available in `train_save_model` and `model_API` files.

Justification

I worked on the provided datasets by Starbucks for this project and then built a model that can predict whether a consumer will finish or browse the offer?

To begin, I looked at each dataset and visualized it to gain a better grasp of the data. Then I moved on to the Preprocessing Section, which consumed the majority of my time and work. After that, I experimented with many models to find which one worked best in this situation.

I got the following insights from the datasets:

- The most popular offers are BOGO and discount.
- When compared to O, F & M have the highest revenue.
- The duration of the offer and the level of difficulty are the most correlated elements to the target feature.

Reflection & Improvement

I had a lot of fun working on this capstone project because it allowed me to improve my data preprocessing and modeling skills. The end-to-end problem solution steps, include the following:

1. Recognizing the issue and deciding to focus on the client response for each offer.
2. Importing three datasets was the first step.
3. Investigating each dataset and its characteristics.
4. Visualizing the ambiguous features in order to comprehend their impact
5. Preprocessing all datasets and writing step-by-step instructions.
6. Choosing the attributes of the model
7. Experiment with various models.
8. Assessing the model's output.
9. Fine-tuning the optimal model parameters
10. Building an API to test the model interactively is number ten.

The data preprocessing was, in my opinion, the most challenging portion.

Further improvement that could also be created to solve the following statemetns related with this data set:

- Creating a model that predicts which offers should be sent to which customers?
- Creating a model that can predict which clients will purchase in every situation

In [ ]: