Starbucks_Capstone_Project

December 22, 2019

1 Starbucks Capstone Challenge

1.1 1. Definition

1.1.1 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.

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.

1.1.2 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.

1.1.3 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.

1.1.4 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).

1.1.5 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.

1.1.6 Problem Statement

The problem is simple: we want to make better purchasing offers to Starbucks' customers. For this, we can use customer's past behaviour to find patterns and try to be more assertive. As given by the Udacity's Starbucks Project Overview, the basic task is to use the data to identify which groups of people are most responsive to each type of offer, and how best to present each type of offer. In other words, this is a classification problem where the model takes user behaviour data as input and produces a group as output (either previously defined or not).

This has been one of the most used applications of machine learning in the industry, since it provides you with means to save money spent on marketing campaigns by directing content to users who are more likely to convert based on a multitude of characteristics.

1.1.7 Metrics

To evaluate the trained models, we'll compare the models based on it's F1-Score. This is a widely used metric to evaluate classification problems. Aditya Mishra defines it as follows: > F1 Score is the Harmonic Mean between precision and recall. The range for F1 Score is [0, 1]. It tells you how precise your classifier is (how many instances it classifies correctly), as well as how robust it is (it does not miss a significant number of instances).

Since the F1-Score is a weighted average of the precision and recall metrics, it works well to evaluate datasets that aren't very well balanced.

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

from sklearn import metrics
from sklearn.preprocessing import MultiLabelBinarizer, LabelEncoder
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.dummy import DummyClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn import svm
from sklearn.tree import DecisionTreeClassifier
from datetime import datetime

%matplotlib inline
```

[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)
```

1.1.8 portfolio dataset preparation

[3]:
```
portfolio.shape
```

[3]:
```
(10, 6)
```

[4]:
```
portfolio.dtypes
```

[4]:
```
channels      object
difficulty     int64
duration       int64
id            object
offer_type    object
reward         int64
dtype: object
```

[5]:
```
portfolio.head(10)
```

[5]:
```
                       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
0  ae264e3637204a6fb9bb56bc8210ddfd           bogo      10
1  4d5c57ea9a6940dd891ad53e9dbe8da0           bogo      10
2  3f207df678b143eea3cee63160fa8bed  informational       0
3  9b98b8c7a33c4b65b9aebfe6a799e6d9           bogo       5
4  0b1e1539f2cc45b7b9fa7c272da2e1d7       discount       5
5  2298d6c36e964ae4a3e7e9706d1fb8c2       discount       3
6  fafdcd668e3743c1bb461111dcafc2a4       discount       2
7  5a8bc65990b245e5a138643cd4eb9837  informational       0
8  f19421c1d4aa40978ebb69ca19b0e20d           bogo       5
9  2906b810c7d4411798c6938adc9daaa5       discount       2
```

We can see some variables that could use some preprocessing, such as `channels` which is a list of values. We'll use Scikit-learn's MultiLabelBinarizer to transform it.

Then we'll create a copy of the original `portfolio` dataset with the new encoded columns.

[6]:
```python
mlb = MultiLabelBinarizer()
encoded_channels = mlb.fit_transform(portfolio['channels'])
```

[7]:
```python
encoded_channels_df = pd.DataFrame(encoded_channels,
                                   columns = mlb.classes_,
                                   index = portfolio['channels'].index)
```

[8]:
```python
processed_portfolio = portfolio.copy()

processed_portfolio = processed_portfolio.join(encoded_channels_df)
```

[9]:
```python
processed_portfolio = processed_portfolio.drop('channels', axis = 1)
print(processed_portfolio)
```

```
   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  fafdcd668e3743c1bb461111dcafc2a4       discount
7           0         3  5a8bc65990b245e5a138643cd4eb9837  informational
8           5         5  f19421c1d4aa40978ebb69ca19b0e20d           bogo
9          10         7  2906b810c7d4411798c6938adc9daaa5       discount

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

[10]:
```python
processed_portfolio.isna().sum()
```

[10]:
```
difficulty    0
duration      0
id            0
offer_type    0
reward        0
email         0
mobile        0
```

```
social        0
web           0
dtype: int64
```

No empty cells, looks like this dataset is good enough for now.

1.1.9 profile dataset preparation

[11]:
```
profile.shape
```

[11]:
```
(17000, 5)
```

[12]:
```
profile.dtypes
```

[12]:
```
age                   int64
became_member_on      int64
gender               object
id                   object
income              float64
dtype: object
```

[13]:
```
profile.head(10)
```

[13]:

	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
5	68	20180426	M	e2127556f4f64592b11af22de27a7932	70000.0
6	118	20170925	None	8ec6ce2a7e7949b1bf142def7d0e0586	NaN
7	118	20171002	None	68617ca6246f4fbc85e91a2a49552598	NaN
8	65	20180209	M	389bc3fa690240e798340f5a15918d5c	53000.0
9	118	20161122	None	8974fc5686fe429db53ddde067b88302	NaN

The `profile` dataset has some interesting characteristics, such as: * `NaN` values for the `income` column. * `None` value for the `gender`column (which is ok, since there are more genders than M, F, but this might need to be treated since we have `O` value - that probably means 'others'). * `became_member_on` has dates that are treated as numbers. * `age` has the value `118` repeated several times. Since it's fairly unlikely for the customers to be 118 years-old, I'm assuming this is also some kind of previous data preprocessing and won't change it.

[14]:
```
profile['gender'].unique()
```

[14]:
```
array([None, 'F', 'M', 'O'], dtype=object)
```

[15]:
```
profile.isna().sum()
```

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

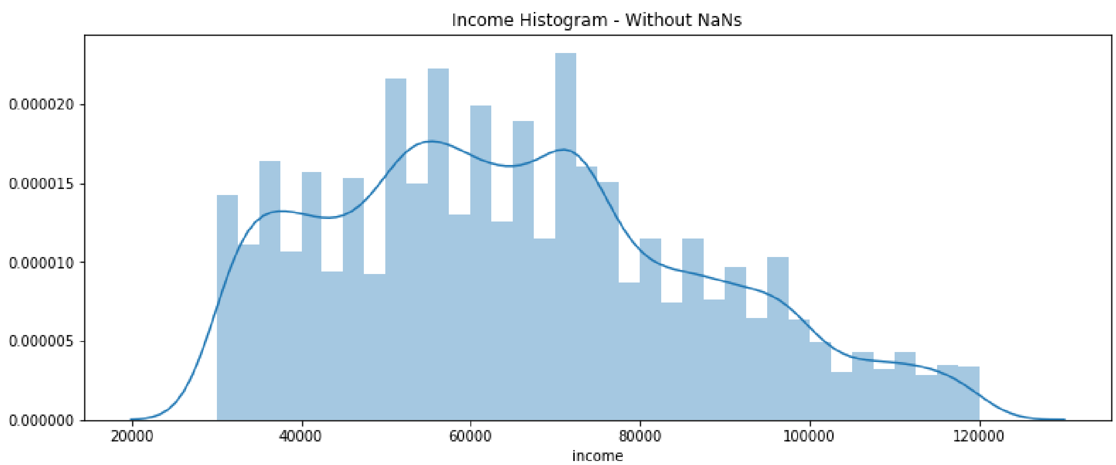
The `None` value for `gender` is not understood as a value, so it needs treatment. We'll fill the `None` values with `Unknown`.

[16]:
```python
processed_profile = profile.copy()

processed_profile['gender'].fillna('Unknown', inplace = True)
```

For the `income` column, let's see what's the data distribution without the `NaN`s:

[17]:
```python
plt.figure(figsize = (13, 5))
sns.distplot(profile['income'].dropna());
plt.title('Income Histogram - Without NaNs');
```



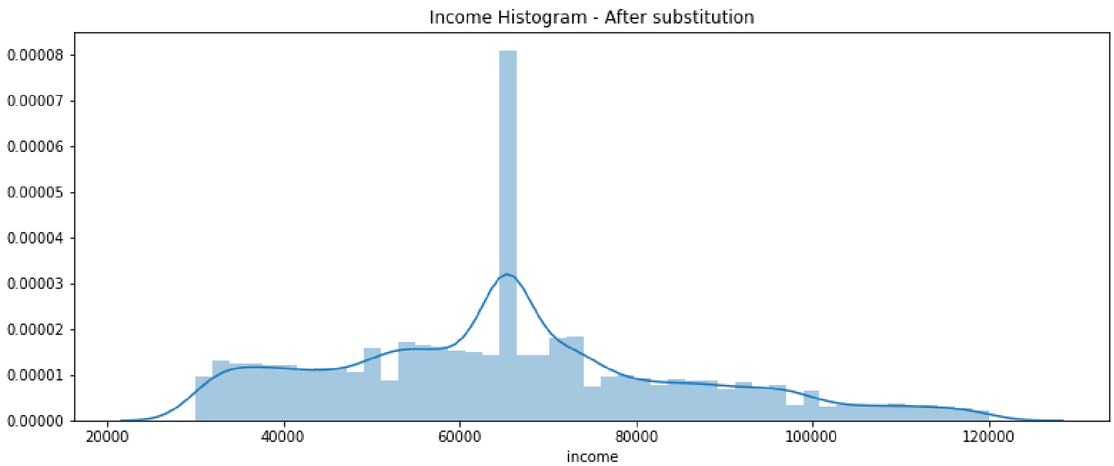
[18]:
```python
profile['income'].describe()
```

[18]:
```
count     14825.000000
mean      65404.991568
std       21598.299410
min       30000.000000
25%       49000.000000
50%       64000.000000
75%       80000.000000
max      120000.000000
Name: income, dtype: float64
```

By filling the NaNs with some value, we'll change the distribution's shape. Since both mean and median are fairly close to each other, it doesn't matter much which one we'll use. I chose the mean.

[19]:
```
processed_profile['income'].fillna(profile['income'].mean(), inplace = True)
```

[20]:
```
plt.figure(figsize = (13, 5))
sns.distplot(processed_profile['income']);
plt.title('Income Histogram - After substitution');
```



We can see it changed a bit the distribution of the data, but we were already expecting that.

[21]:
```
processed_profile.isna().sum()
```

[21]:
```
age                 0
became_member_on    0
gender              0
id                  0
income              0
dtype: int64
```

No empty cells, looks like this dataset is good enough for now.

Another alteration we can work on is to transform the `became_member_on` column into a `datetime` object column, which allows us to work with time windows. This means that we can get the information for how long a customer has been a member of the program. Since we don't really know when those campaigns were build, we don't have a specifict point in time to measure a customer's "age" as a customer. On the other hand, we can simply use the year the user signed up for the membership.

[22]:
```
def convert_to_date(date_element):
    return datetime.strptime(str(date_element), '%Y%m%d')
```

[23]:
```
became_member_on_date = processed_profile['became_member_on'].
↪apply(convert_to_date)
```

[24]:
```
became_member_on_date.head()
```

[24]:
```
0   2017-02-12
1   2017-07-15
2   2018-07-12
3   2017-05-09
4   2017-08-04
Name: became_member_on, dtype: datetime64[ns]
```

[25]:
```
became_member_on_year = became_member_on_date.apply(lambda date_point:␣
↪date_point.year)
```

[26]:
```
processed_profile['became_member_on_year'] = became_member_on_year
```

[27]:
```
processed_profile = processed_profile.drop(['became_member_on'], axis = 1)
```

[28]:
```
processed_profile.head()
```

[28]:
```
   age   gender                                id         income  \
0  118  Unknown  68be06ca386d4c31939f3a4f0e3dd783   65404.991568
1   55        F  0610b486422d4921ae7d2bf64640c50b  112000.000000
2  118  Unknown  38fe809add3b4fcf9315a9694bb96ff5   65404.991568
3   75        F  78afa995795e4d85b5d9ceeca43f5fef  100000.000000
4  118  Unknown  a03223e636434f42ac4c3df47e8bac43   65404.991568

   became_member_on_year
0                   2017
1                   2017
2                   2018
3                   2017
4                   2017
```

1.1.10 transcript dataset preparation

[29]:
```
transcript.shape
```

[29]:
```
(306534, 4)
```

[30]:
```
transcript.dtypes
```

[30]:
```
event     object
person    object
time       int64
value     object
```

```
dtype: object
```

[31]:
```
transcript.isna().sum()
```

[31]:
```
event     0
person    0
time      0
value     0
dtype: int64
```

[32]:
```
transcript.sample(10)
```

[32]:
```
                  event                            person  time  \
76581   offer viewed  ffdefcac307f4ca99ac1ebd51470f106   186
30709    transaction  885d8e7de35e4b7abb7c6f494c82c271    48
87734    transaction  25a6a2df56ba4a4a9ad898dbf083c6b5   222
106692  offer viewed  8d20cb72c43c43699ff1074fd1e7d468   306
19710   offer viewed  95dc4202ae22461d865b13da40b3d557    12
103990   transaction  c1dc09fa7f5940a38c2f393f89cb4a50   294
36890    transaction  b3883064435140ce8feac3c1da259948    72
180137   transaction  eae57eab7df940d898b5b32d968ecdc7   438
185351   transaction  3977011340cf47d08a23c4b3d6f6aef6   450
197364   transaction  c0bbc13872474c63a83e8b503bb88f72   486

                                                   value
76581   {'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}
30709                                 {'amount': 7.03}
87734                                {'amount': 13.44}
106692  {'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}
19710   {'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}
103990                  {'amount': 1.1400000000000001}
36890                                 {'amount': 4.93}
180137                                {'amount': 7.78}
185351                                {'amount': 0.66}
197364                               {'amount': 35.26}
```

This dataset has no empty values. The `value` column has a dictionary that has different keys and values. It will be easier to have this column expanded into multiple columns to work with the events.

[33]:
```
value_expanded = transcript['value'].apply(pd.Series)
value_expanded.head()
```

[33]:
```
                           offer id  amount offer_id  reward
0  9b98b8c7a33c4b65b9aebfe6a799e6d9     NaN      NaN     NaN
1  0b1e1539f2cc45b7b9fa7c272da2e1d7     NaN      NaN     NaN
2  2906b810c7d4411798c6938adc9daaa5     NaN      NaN     NaN
```

```
3  fafdcd668e3743c1bb461111dcafc2a4     NaN      NaN     NaN
4  4d5c57ea9a6940dd891ad53e9dbe8da0     NaN      NaN     NaN
```

Now that we have this matrix, we can include it to the rest of the transcript data.

[34]:
```python
transcript_expanded = pd.concat([transcript, value_expanded], axis = 1)
```

[35]:
```python
transcript_expanded.sample(10)
```

[35]:
```
                  event                            person  time  \
97082       transaction  98ba686b0d9943279f4ef1ee9480eaff   258
89483       transaction  35faf6c136ac4eff95cb298191d4dcbe   228
263829     offer viewed  eb9e4fd1814b4fba9cdff0eb00f35278   582
58191    offer received  c77f073996314357b57c8765e85d0a01   168
2724     offer received  cd0cb9d1599c47a0bb69c49d19c2117f     0
176516  offer completed  dcadc299e3914526acf3eac4815b7930   426
228763      transaction  777a1d8f93bb4884829eead23fd6fb53   528
201361      transaction  83b26151b9c9487d897a67be32d2eba4   498
169536      transaction  6c0f89d1092545bbb522281d8337dd2b   414
13088   offer completed  1ba58dab3cae4787ad26d8d77ab7380f     0

                                                   value  \
97082                                   {'amount': 6.82}
89483                                   {'amount': 5.42}
263829   {'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}
58191    {'offer id': '2298d6c36e964ae4a3e7e9706d1fb8c2'}
2724     {'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}
176516  {'offer_id': '2298d6c36e964ae4a3e7e9706d1fb8c2…
228763                                 {'amount': 13.97}
201361                                 {'amount': 11.76}
169536                                 {'amount': 12.12}
13088   {'offer_id': 'f19421c1d4aa40978ebb69ca19b0e20d…

                                offer id  amount  \
97082                                NaN    6.82
89483                                NaN    5.42
263829  f19421c1d4aa40978ebb69ca19b0e20d     NaN
58191   2298d6c36e964ae4a3e7e9706d1fb8c2     NaN
2724    4d5c57ea9a6940dd891ad53e9dbe8da0     NaN
176516                               NaN     NaN
228763                               NaN   13.97
201361                               NaN   11.76
169536                               NaN   12.12
13088                                NaN     NaN

                                offer_id  reward
97082                                NaN     NaN
```

```
89483                                   NaN     NaN
263829                                  NaN     NaN
58191                                   NaN     NaN
2724                                    NaN     NaN
176516  2298d6c36e964ae4a3e7e9706d1fb8c2     3.0
228763                                  NaN     NaN
201361                                  NaN     NaN
169536                                  NaN     NaN
13088   f19421c1d4aa40978ebb69ca19b0e20d     5.0
```

Now we can manipulate this dataset in order to clean it. We will deal with the duplicate `offer id`/`offer_id` column and remove unecessary columns.

The `offer id`/`offer_id` duplicates seem to relate to the same information, but for different events, which means that each line can never have two values for `offer id`/`offer_id` (only one per line). To treat that, we can create a single column thar receives the presented `offer id`/`offer_id` value when one exists.

[36]:
```
transcript_expanded['offer_id_redux'] = np.where(transcript_expanded['offer␣
↪id'].isnull() & transcript_expanded['offer_id'].notnull(),
                                                              ␣
↪transcript_expanded['offer_id'],
                                                              transcript_expanded['offer␣
↪id'])
```

Now we can drop unnecessary columns.

[37]:
```
transcript_expanded = transcript_expanded.drop(['value',
                                                'offer id',
                                                'offer_id'],
                                               axis = 1)
```

[38]:
```
transcript_expanded.head()
```

[38]:
```
            event                            person  time  amount  reward  \
0  offer received  78afa995795e4d85b5d9ceeca43f5fef     0     NaN     NaN
1  offer received  a03223e636434f42ac4c3df47e8bac43     0     NaN     NaN
2  offer received  e2127556f4f64592b11af22de27a7932     0     NaN     NaN
3  offer received  8ec6ce2a7e7949b1bf142def7d0e0586     0     NaN     NaN
4  offer received  68617ca6246f4fbc85e91a2a49552598     0     NaN     NaN

                     offer_id_redux
0  9b98b8c7a33c4b65b9aebfe6a799e6d9
1  0b1e1539f2cc45b7b9fa7c272da2e1d7
2  2906b810c7d4411798c6938adc9daaa5
3  fafdcd668e3743c1bb461111dcafc2a4
4  4d5c57ea9a6940dd891ad53e9dbe8da0
```

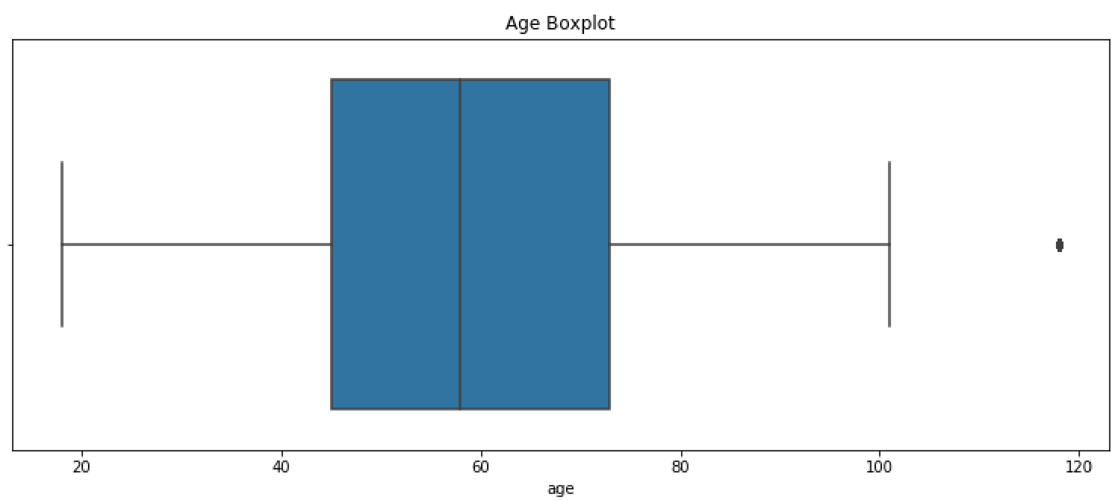
1.2 Exploratory Data Analysis

Starting with the `profile` dataset, we can check a bit of the age and income of the customers.

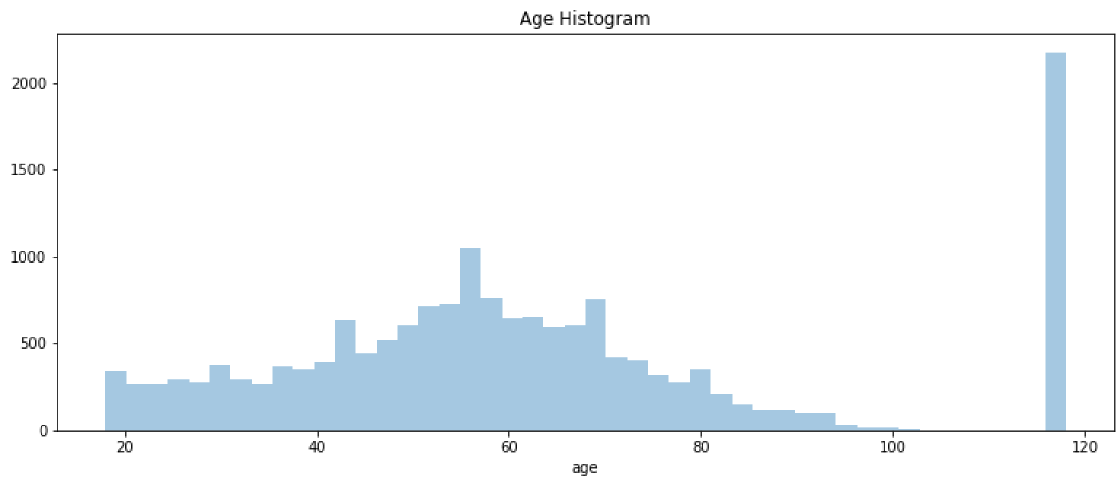
[39]:
```
processed_profile['age'].describe()
```

[39]:
```
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
```

[40]:
```
plt.figure(figsize = (13, 5))
sns.boxplot(processed_profile['age']);
plt.title('Age Boxplot');
```



[41]:
```
plt.figure(figsize = (13, 5))
sns.distplot(processed_profile['age'], kde = False);
plt.title('Age Histogram');
```

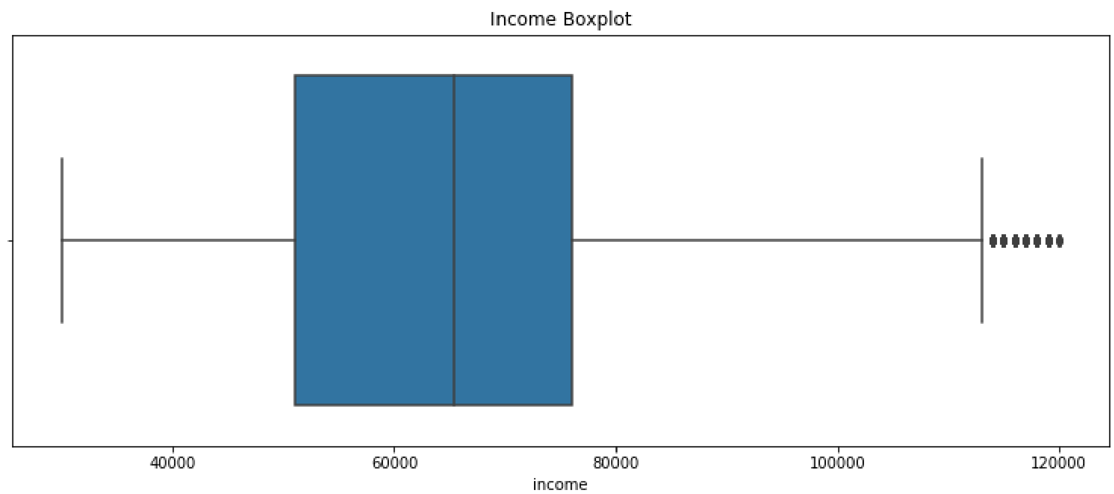


This histogram and the boxplot show us a great amount of outliers near 120. That was expected, since we decided not to treat the `118` values (as discussed earlier). The users are mostly adults, with ages between 40 and 80 and the median in a bit lower than 60 (which is also lower than the mean, that is 62.5).

[42]:
```
processed_profile['income'].describe()
```

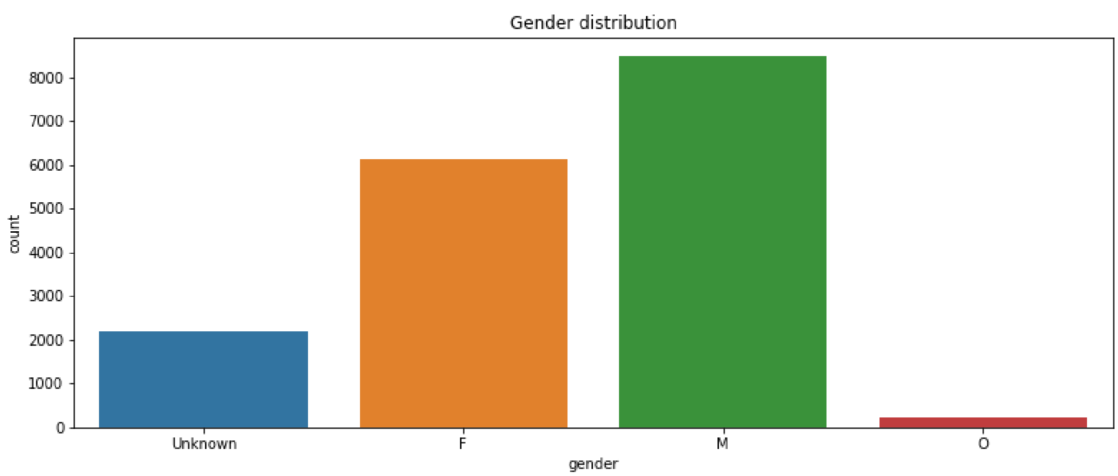
[42]:
```
count     17000.000000
mean      65404.991568
std       20169.288288
min       30000.000000
25%       51000.000000
50%       65404.991568
75%       76000.000000
max      120000.000000
Name: income, dtype: float64
```

[43]:
```
plt.figure(figsize = (13, 5))
sns.boxplot(processed_profile['income']);
plt.title('Income Boxplot');
```



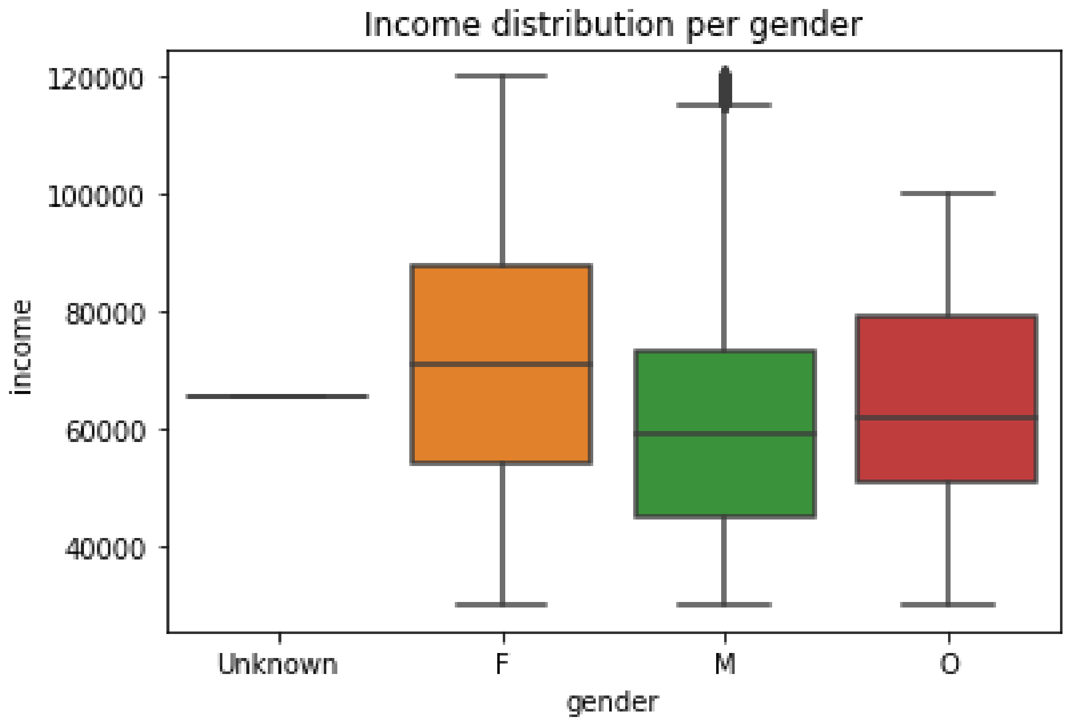
We already saw the histogram for this data,the boxplot shows the distribution is a bit skewed. Mean and median seem close (around $65,000) and most of the data is between $60,000 and $75,000.

[44]:
```
plt.figure(figsize = (13, 5))
sns.countplot(processed_profile['gender']);
plt.title('Gender distribution');
```



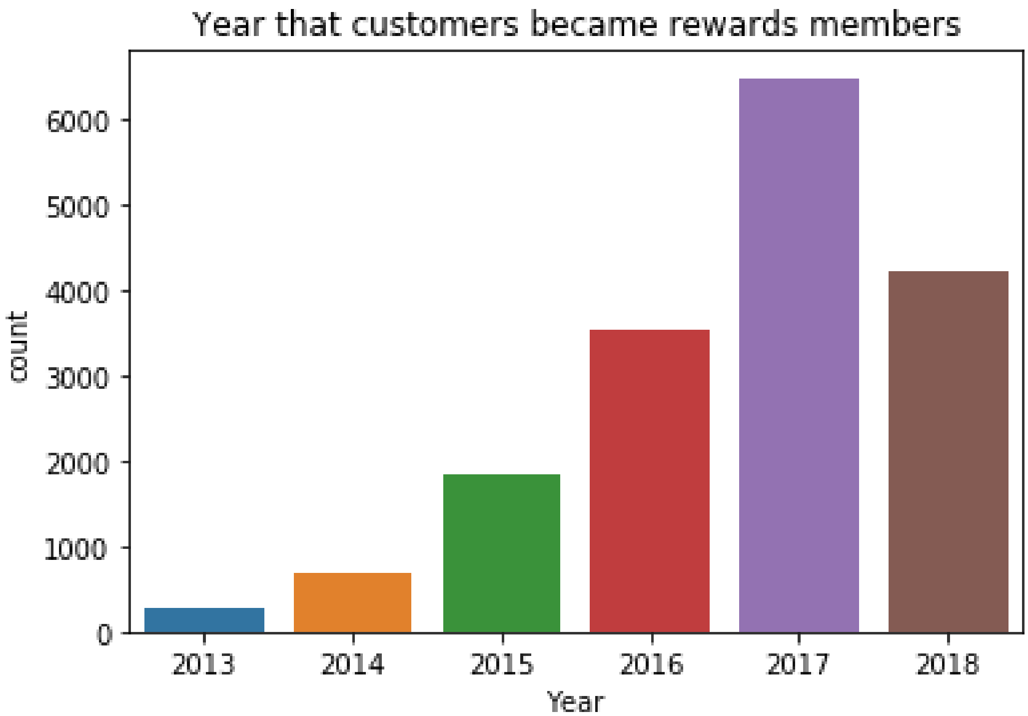
There are more male than females in the dataset. There is a large amount of `Unknown` and a few 'others'.

[45]:
```
sns.boxplot(x = 'gender',
            y = 'income',
            data = processed_profile);
plt.title('Income distribution per gender');
```



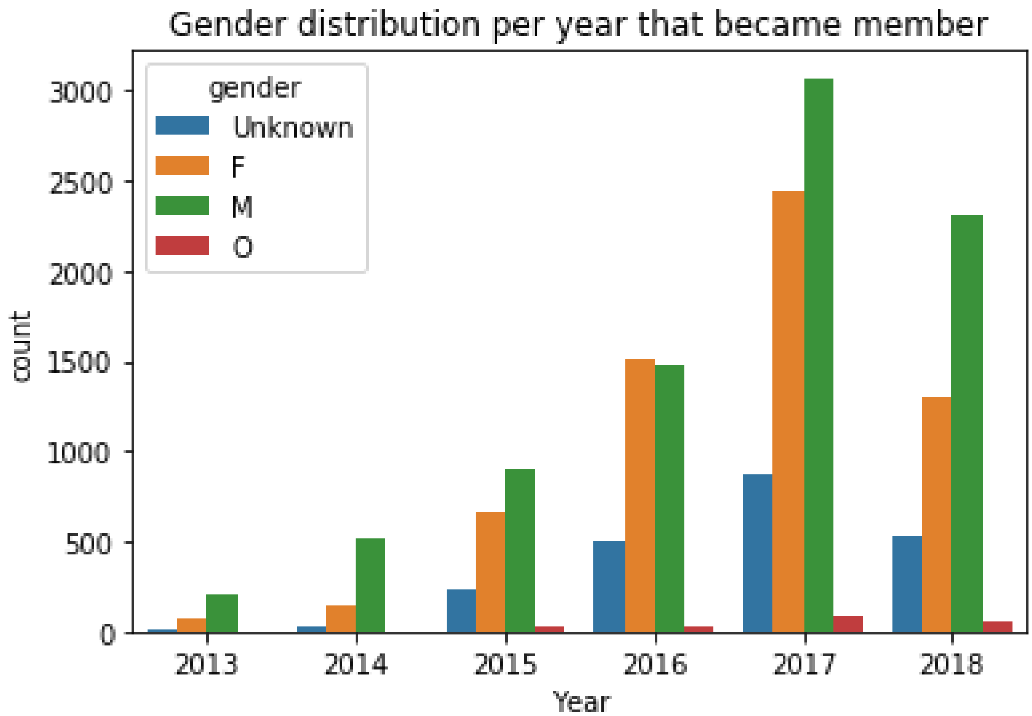
The boxplots show there is no evidence that the income differs accross genders.

[46]:
```
sns.countplot('became_member_on_year',
              data = processed_profile);
plt.title('Year that customers became rewards members')
plt.xlabel('Year');
```



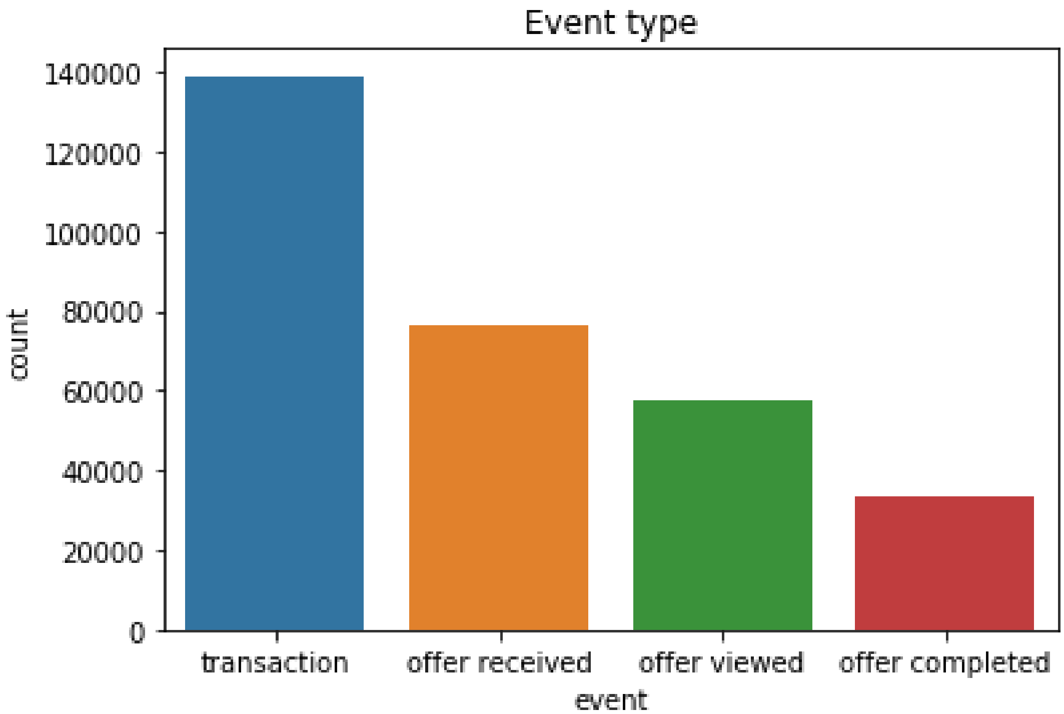
More customers became members in 2017, followed by 2018 then 2016. The first year the with records is 2013 and it's also the year with fewer members signing for the program.

[47]:
```
sns.countplot(x = 'became_member_on_year',
              hue = 'gender',
              data = processed_profile);
plt.xlabel('Year');
plt.title('Gender distribution per year that became member');
```



In all years, there are either more male members signing up for the program (with exception of 2016, in which there were slight more female members registrations).

[48]:
```
sns.countplot(transcript_expanded['event'],
              order = transcript_expanded['event'].value_counts().index);
plt.title('Event type');
```



The event type that is most frequent is `transaction`, followed by `offer received`, `offer viewed` and `offer completed`. This makes sense, since it looks like a usual customer funnel for marketing.

1.3 Merging datasets and data preprocessing

We can get add more information to the `transcript_expanded` dataset by joining it to the `processed_portfolio` dataset, that contains information on the offers.

[49]:
```
transcript_with_portfolio = transcript_expanded.merge(processed_portfolio,
                                                      how = 'left',
                                                      left_on =␣
 ↪'offer_id_redux',
                                                      right_on = 'id')
```

[50]:
```
# sort dataset by user and time, to make it easier for humans to see data
transcript_with_portfolio = transcript_with_portfolio.sort_values(['person',␣
 ↪'time'])
```

[51]:
```
transcript_with_portfolio.groupby(['event', 'offer_type'])['offer_type'].count()
```

[51]:
```
event            offer_type
offer completed  bogo          15669
                 discount      17910
offer received   bogo          30499
```

```
                  discount          30543
                  informational     15235
offer viewed      bogo              25449
                  discount          21445
                  informational     10831
Name: offer_type, dtype: int64
```

BOGO and discount offers are the inly ones with an associated `offer completed` event. Also, the `transaction` event doesn't have an associated id, which means that the join won't add data to those.

Basically, we can look into the BOGO and discount offers user funnels in this order: * offer received * offer viewed * transaction * offer completed

For the informational offer, the funnel has this order: * offer received * offer viewed * transaction

This means that we have to find a way to add the transaction data into the funnel. This can be done through the user id and the timestamp. If a user didn't get to the transaction part, it won't have an `offer completed` event as well. For the informational offer, the transaction data will only exist if it came after the `offer viewed` event. The timestamp will help us find the "organic" users: users that became members regardless of the campaigns. All those scenarios can be found by ordering data by time, offer id, person and event.

[52]:
```
view_to_complete = transcript_with_portfolio[['time', 'offer_id_redux',␣
↪'person', 'event']][(transcript_with_portfolio['event']=='transaction') |␣
↪(transcript_with_portfolio['event'] == 'offer viewed')].
↪groupby(['person','offer_id_redux'])
```

[53]:
```
view_to_complete.head()
```

[53]:
```
        time                    offer_id_redux  \
77705    192  5a8bc65990b245e5a138643cd4eb9837
89291    228                               NaN
139992   372  3f207df678b143eea3cee63160fa8bed
168412   414                               NaN
187554   456  f19421c1d4aa40978ebb69ca19b0e20d
228422   528                               NaN
233413   540  fafdcd668e3743c1bb461111dcafc2a4
237784   552                               NaN
258883   576                               NaN
85769    216  f19421c1d4aa40978ebb69ca19b0e20d
284472   630  f19421c1d4aa40978ebb69ca19b0e20d
16179      6  3f207df678b143eea3cee63160fa8bed
75427    186  2298d6c36e964ae4a3e7e9706d1fb8c2
133370   354  5a8bc65990b245e5a138643cd4eb9837
177937   432  0b1e1539f2cc45b7b9fa7c272da2e1d7
222679   516  9b98b8c7a33c4b65b9aebfe6a799e6d9
18431     12  fafdcd668e3743c1bb461111dcafc2a4
174774   426  4d5c57ea9a6940dd891ad53e9dbe8da0
```

293372	660	5a8bc65990b245e5a138643cd4eb9837
67584	168	2298d6c36e964ae4a3e7e9706d1fb8c2
131476	348	f19421c1d4aa40978ebb69ca19b0e20d
165442	408	5a8bc65990b245e5a138643cd4eb9837
263808	582	9b98b8c7a33c4b65b9aebfe6a799e6d9
27148	36	5a8bc65990b245e5a138643cd4eb9837
105508	300	fafdcd668e3743c1bb461111dcafc2a4
140716	372	3f207df678b143eea3cee63160fa8bed
173080	420	fafdcd668e3743c1bb461111dcafc2a4
27263	36	5a8bc65990b245e5a138643cd4eb9837
76441	186	fafdcd668e3743c1bb461111dcafc2a4
219332	510	f19421c1d4aa40978ebb69ca19b0e20d
…	…	…
26549	36	fafdcd668e3743c1bb461111dcafc2a4
72825	180	4d5c57ea9a6940dd891ad53e9dbe8da0
269576	594	f19421c1d4aa40978ebb69ca19b0e20d
103669	288	3f207df678b143eea3cee63160fa8bed
148670	396	4d5c57ea9a6940dd891ad53e9dbe8da0
287565	636	3f207df678b143eea3cee63160fa8bed
68851	168	fafdcd668e3743c1bb461111dcafc2a4
132444	348	4d5c57ea9a6940dd891ad53e9dbe8da0
182159	438	f19421c1d4aa40978ebb69ca19b0e20d
221408	510	4d5c57ea9a6940dd891ad53e9dbe8da0
289457	642	ae264e3637204a6fb9bb56bc8210ddfd
16325	6	fafdcd668e3743c1bb461111dcafc2a4
83982	210	9b98b8c7a33c4b65b9aebfe6a799e6d9
233587	540	5a8bc65990b245e5a138643cd4eb9837
23028	24	fafdcd668e3743c1bb461111dcafc2a4
73167	180	4d5c57ea9a6940dd891ad53e9dbe8da0
168973	414	ae264e3637204a6fb9bb56bc8210ddfd
226096	522	fafdcd668e3743c1bb461111dcafc2a4
177513	432	fafdcd668e3743c1bb461111dcafc2a4
293268	660	4d5c57ea9a6940dd891ad53e9dbe8da0
15591	6	f19421c1d4aa40978ebb69ca19b0e20d
65899	168	5a8bc65990b245e5a138643cd4eb9837
218451	510	f19421c1d4aa40978ebb69ca19b0e20d
294735	666	9b98b8c7a33c4b65b9aebfe6a799e6d9
15836	6	fafdcd668e3743c1bb461111dcafc2a4
69626	174	0b1e1539f2cc45b7b9fa7c272da2e1d7
133074	354	2906b810c7d4411798c6938adc9daaa5
168022	414	2906b810c7d4411798c6938adc9daaa5
230690	534	9b98b8c7a33c4b65b9aebfe6a799e6d9
262475	582	2906b810c7d4411798c6938adc9daaa5

	person	event
77705	0009655768c64bdeb2e877511632db8f	offer viewed
89291	0009655768c64bdeb2e877511632db8f	transaction

139992	0009655768c64bdeb2e877511632db8f	offer viewed
168412	0009655768c64bdeb2e877511632db8f	transaction
187554	0009655768c64bdeb2e877511632db8f	offer viewed
228422	0009655768c64bdeb2e877511632db8f	transaction
233413	0009655768c64bdeb2e877511632db8f	offer viewed
237784	0009655768c64bdeb2e877511632db8f	transaction
258883	0009655768c64bdeb2e877511632db8f	transaction
85769	00116118485d4dfda04fdbaba9a87b5c	offer viewed
284472	00116118485d4dfda04fdbaba9a87b5c	offer viewed
16179	0011e0d4e6b944f998e987f904e8c1e5	offer viewed
75427	0011e0d4e6b944f998e987f904e8c1e5	offer viewed
133370	0011e0d4e6b944f998e987f904e8c1e5	offer viewed
177937	0011e0d4e6b944f998e987f904e8c1e5	offer viewed
222679	0011e0d4e6b944f998e987f904e8c1e5	offer viewed
18431	0020c2b971eb4e9188eac86d93036a77	offer viewed
174774	0020c2b971eb4e9188eac86d93036a77	offer viewed
293372	0020c2b971eb4e9188eac86d93036a77	offer viewed
67584	0020ccbbb6d84e358d3414a3ff76cffd	offer viewed
131476	0020ccbbb6d84e358d3414a3ff76cffd	offer viewed
165442	0020ccbbb6d84e358d3414a3ff76cffd	offer viewed
263808	0020ccbbb6d84e358d3414a3ff76cffd	offer viewed
27148	003d66b6608740288d6cc97a6903f4f0	offer viewed
105508	003d66b6608740288d6cc97a6903f4f0	offer viewed
140716	003d66b6608740288d6cc97a6903f4f0	offer viewed
173080	003d66b6608740288d6cc97a6903f4f0	offer viewed
27263	00426fe3ffde4c6b9cb9ad6d077a13ea	offer viewed
76441	00426fe3ffde4c6b9cb9ad6d077a13ea	offer viewed
219332	004b041fbfe44859945daa2c7f79ee64	offer viewed
…	…	…
26549	ffede3b700ac41d6a266fa1ba74b4f16	offer viewed
72825	ffede3b700ac41d6a266fa1ba74b4f16	offer viewed
269576	ffede3b700ac41d6a266fa1ba74b4f16	offer viewed
103669	fff0f0aac6c547b9b263080f09a5586a	offer viewed
148670	fff0f0aac6c547b9b263080f09a5586a	offer viewed
287565	fff0f0aac6c547b9b263080f09a5586a	offer viewed
68851	fff29fb549084123bd046dbc5ceb4faa	offer viewed
132444	fff29fb549084123bd046dbc5ceb4faa	offer viewed
182159	fff29fb549084123bd046dbc5ceb4faa	offer viewed
221408	fff29fb549084123bd046dbc5ceb4faa	offer viewed
289457	fff29fb549084123bd046dbc5ceb4faa	offer viewed
16325	fff3ba4757bd42088c044ca26d73817a	offer viewed
83982	fff3ba4757bd42088c044ca26d73817a	offer viewed
233587	fff3ba4757bd42088c044ca26d73817a	offer viewed
23028	fff7576017104bcc8677a8d63322b5e1	offer viewed
73167	fff7576017104bcc8677a8d63322b5e1	offer viewed
168973	fff7576017104bcc8677a8d63322b5e1	offer viewed
226096	fff7576017104bcc8677a8d63322b5e1	offer viewed

```
177513  fff8957ea8b240a6b5e634b6ee8eafcf  offer viewed
293268  fff8957ea8b240a6b5e634b6ee8eafcf  offer viewed
15591   fffad4f4828548d1b5583907f2e9906b  offer viewed
65899   fffad4f4828548d1b5583907f2e9906b  offer viewed
218451  fffad4f4828548d1b5583907f2e9906b  offer viewed
294735  fffad4f4828548d1b5583907f2e9906b  offer viewed
15836   ffff82501cea40309d5fdd7edcca4a07  offer viewed
69626   ffff82501cea40309d5fdd7edcca4a07  offer viewed
133074  ffff82501cea40309d5fdd7edcca4a07  offer viewed
168022  ffff82501cea40309d5fdd7edcca4a07  offer viewed
230690  ffff82501cea40309d5fdd7edcca4a07  offer viewed
262475  ffff82501cea40309d5fdd7edcca4a07  offer viewed

[57730 rows x 4 columns]
```

Since the dataset is grouped and ordered, we can simply fill the offer id gaps with the previous value.

[54]:
```
fill_offer_id = view_to_complete['offer_id_redux'].
↪fillna(view_to_complete['offer_id_redux'].ffill()).ffill()
```

Since this column is indexed, we can join it with the original dataset and add the missing values to either one of the redundant columns (we will actually make a new column with the values for sanity check). Then drop the unnecessary columns.

[55]:
```
with_full_offer_id = transcript_with_portfolio.join(fill_offer_id,
                                                     rsuffix = '_right')
```

[56]:
```
with_full_offer_id['offer_id'] = np.where(with_full_offer_id['offer_id_redux'].
↪isnull(),
                                                                              ␣
↪with_full_offer_id['offer_id_redux_right'],
                                          with_full_offer_id['offer_id_redux'])
```

[57]:
```
with_full_offer_id.head()
```

[57]:
```
                 event                            person  time  amount  \
55972   offer received  0009655768c64bdeb2e877511632db8f   168     NaN
77705     offer viewed  0009655768c64bdeb2e877511632db8f   192     NaN
89291      transaction  0009655768c64bdeb2e877511632db8f   228   22.16
113605  offer received  0009655768c64bdeb2e877511632db8f   336     NaN
139992    offer viewed  0009655768c64bdeb2e877511632db8f   372     NaN

        reward_x                    offer_id_redux  difficulty  duration  \
55972        NaN  5a8bc65990b245e5a138643cd4eb9837         0.0       3.0
77705        NaN  5a8bc65990b245e5a138643cd4eb9837         0.0       3.0
89291        NaN                               NaN         NaN       NaN
113605       NaN  3f207df678b143eea3cee63160fa8bed         0.0       4.0
```

```
139992       NaN  3f207df678b143eea3cee63160fa8bed        0.0       4.0

                                      id    offer_type  reward_y  email  \
55972   5a8bc65990b245e5a138643cd4eb9837  informational       0.0    1.0
77705   5a8bc65990b245e5a138643cd4eb9837  informational       0.0    1.0
89291                                NaN            NaN       NaN    NaN
113605  3f207df678b143eea3cee63160fa8bed  informational       0.0    1.0
139992  3f207df678b143eea3cee63160fa8bed  informational       0.0    1.0

        mobile  social  web             offer_id_redux_right  \
55972      1.0     1.0  0.0                              NaN
77705      1.0     1.0  0.0  5a8bc65990b245e5a138643cd4eb9837
89291      NaN     NaN  NaN  5a8bc65990b245e5a138643cd4eb9837
113605     1.0     0.0  1.0                              NaN
139992     1.0     0.0  1.0  3f207df678b143eea3cee63160fa8bed

                                offer_id
55972   5a8bc65990b245e5a138643cd4eb9837
77705   5a8bc65990b245e5a138643cd4eb9837
89291   5a8bc65990b245e5a138643cd4eb9837
113605  3f207df678b143eea3cee63160fa8bed
139992  3f207df678b143eea3cee63160fa8bed
```

[58]:
```
with_full_offer_id = with_full_offer_id.drop(['offer_id_redux',
                                              'offer_id_redux_right'],
                                             axis = 1)
```

[59]:
```
with_full_offer_id.columns
```

[59]:
```
Index(['event', 'person', 'time', 'amount', 'reward_x', 'difficulty',
       'duration', 'id', 'offer_type', 'reward_y', 'email', 'mobile', 'social',
       'web', 'offer_id'],
      dtype='object')
```

Now we can merge it again to get the transaction events data. This means we'll duplicate many columns, but all we have to do is drop them.

[60]:
```
with_transaction = with_full_offer_id.merge(processed_portfolio,
                                            how = 'left',
                                            left_on = 'offer_id',
                                            right_on = 'id')
```

[61]:
```
with_transaction.columns
```

[61]:
```
Index(['event', 'person', 'time', 'amount', 'reward_x', 'difficulty_x',
       'duration_x', 'id_x', 'offer_type_x', 'reward_y', 'email_x', 'mobile_x',
       'social_x', 'web_x', 'offer_id', 'difficulty_y', 'duration_y', 'id_y',
```

```
        'offer_type_y', 'reward', 'email_y', 'mobile_y', 'social_y', 'web_y'],
       dtype='object')
```

[62]:
```
with_transaction[['reward',
                  'reward_x',
                  'reward_y',
                  'difficulty_x',
                  'difficulty_y',
                  'duration_x',
                  'duration_y']]
```

[62]:
```
        reward  reward_x  reward_y  difficulty_x  difficulty_y  duration_x  \
0            0       NaN       0.0           0.0             0         3.0
1            0       NaN       0.0           0.0             0         3.0
2            0       NaN       NaN           NaN             0         NaN
3            0       NaN       0.0           0.0             0         4.0
4            0       NaN       0.0           0.0             0         4.0
5            5       NaN       5.0           5.0             5         5.0
6            0       NaN       NaN           NaN             0         NaN
7            5       5.0       5.0           5.0             5         5.0
8            5       NaN       5.0           5.0             5         5.0
9            2       NaN       2.0          10.0            10        10.0
10           5       NaN       NaN           NaN             5         NaN
11           2       2.0       2.0          10.0            10        10.0
12           2       NaN       2.0          10.0            10        10.0
13           2       NaN       NaN           NaN            10         NaN
14           2       NaN       2.0          10.0            10         7.0
15           2       NaN       NaN           NaN            10         NaN
16           2       2.0       2.0          10.0            10         7.0
17           2       NaN       NaN           NaN            10         NaN
18           2       NaN       NaN           NaN            10         NaN
19           2       NaN       NaN           NaN            10         NaN
20           5       NaN       5.0           5.0             5         5.0
21           5       NaN       5.0           5.0             5         5.0
22           5       NaN       NaN           NaN             5         NaN
23           5       NaN       NaN           NaN             5         NaN
24           5       NaN       NaN           NaN             5         NaN
25           5       NaN       5.0           5.0             5         5.0
26           5       NaN       5.0           5.0             5         5.0
27           0       NaN       0.0           0.0             0         4.0
28           0       NaN       0.0           0.0             0         4.0
29           0       NaN       NaN           NaN             0         NaN
…          …        …         …            …            …          …
306504       2       2.0       2.0          10.0            10        10.0
306505       2       NaN       NaN           NaN            10         NaN
306506       2       NaN       NaN           NaN            10         NaN
306507       5       NaN       5.0          20.0            20        10.0
```

306508	5	NaN	5.0	20.0	20	10.0
306509	5	NaN	NaN	NaN	20	NaN
306510	5	5.0	5.0	20.0	20	10.0
306511	5	NaN	NaN	NaN	20	NaN
306512	5	NaN	NaN	NaN	20	NaN
306513	5	NaN	NaN	NaN	20	NaN
306514	5	NaN	NaN	NaN	20	NaN
306515	2	NaN	2.0	10.0	10	7.0
306516	2	NaN	2.0	10.0	10	7.0
306517	2	NaN	NaN	NaN	10	NaN
306518	2	2.0	2.0	10.0	10	7.0
306519	2	NaN	2.0	10.0	10	7.0
306520	2	NaN	2.0	10.0	10	7.0
306521	2	NaN	NaN	NaN	10	NaN
306522	2	2.0	2.0	10.0	10	7.0
306523	2	NaN	NaN	NaN	10	NaN
306524	5	NaN	5.0	5.0	5	7.0
306525	2	NaN	NaN	NaN	10	NaN
306526	5	5.0	5.0	5.0	5	7.0
306527	5	NaN	5.0	5.0	5	7.0
306528	2	NaN	2.0	10.0	10	7.0
306529	5	NaN	NaN	NaN	5	NaN
306530	2	2.0	2.0	10.0	10	7.0
306531	2	NaN	2.0	10.0	10	7.0
306532	2	NaN	NaN	NaN	10	NaN
306533	2	NaN	NaN	NaN	10	NaN

	duration_y
0	3
1	3
2	3
3	4
4	4
5	5
6	4
7	5
8	5
9	10
10	5
11	10
12	10
13	10
14	7
15	10
16	7
17	10
18	10

```
19                10
20                 5
21                 5
22                 5
23                 5
24                 5
25                 5
26                 5
27                 4
28                 4
29                 4
…              …
306504            10
306505            10
306506            10
306507            10
306508            10
306509            10
306510            10
306511            10
306512            10
306513            10
306514            10
306515             7
306516             7
306517             7
306518             7
306519             7
306520             7
306521             7
306522             7
306523             7
306524             7
306525             7
306526             7
306527             7
306528             7
306529             7
306530             7
306531             7
306532             7
306533             7

[306534 rows x 7 columns]
```

[63]:

```python
with_transaction[['reward',
                  'reward_x',
```

```
                    'reward_y',
                    'difficulty_x',
                    'difficulty_y',
                    'duration_x',
                    'duration_y']].isnull().sum()
```

[63]:
```
reward               0
reward_x        272955
reward_y        138953
difficulty_x    138953
difficulty_y         0
duration_x      138953
duration_y           0
dtype: int64
```

We'll keep the `reward_y` column instead of the other ones because the lack of information there is related to the event type.

[64]:
```
with_transaction.columns
```

[64]:
```
Index(['event', 'person', 'time', 'amount', 'reward_x', 'difficulty_x',
       'duration_x', 'id_x', 'offer_type_x', 'reward_y', 'email_x', 'mobile_x',
       'social_x', 'web_x', 'offer_id', 'difficulty_y', 'duration_y', 'id_y',
       'offer_type_y', 'reward', 'email_y', 'mobile_y', 'social_y', 'web_y'],
      dtype='object')
```

[65]:
```
with_transaction = with_transaction.drop(['reward',
                                          'reward_x',
                                          'difficulty_x',
                                          'duration_x',
                                          'id_x',
                                          'id_y',
                                          'offer_type_x',
                                          'email_x',
                                          'mobile_x',
                                          'social_x',
                                          'web_x'
                                         ],
                                         axis = 1)
with_transaction.columns
```

[65]:
```
Index(['event', 'person', 'time', 'amount', 'reward_y', 'offer_id',
       'difficulty_y', 'duration_y', 'offer_type_y', 'email_y', 'mobile_y',
       'social_y', 'web_y'],
      dtype='object')
```

[66]:
```
with_transaction = with_transaction.rename(columns = {'reward_y': 'reward',
                                                      'difficulty_y':␣
 ↪'difficulty',
                                                      'duration_y': 'duration',
                                                      'offer_type_y':␣
 ↪'offer_type',
                                                      'email_y': 'email',
                                                      'mobile_y': 'mobile',
                                                      'social_y': 'social',
                                                      'web_y': 'web'
                                                     })
```

[67]:
```
with_transaction.head()
```

[67]:
```
            event                            person  time  amount  reward  \
0  offer received  0009655768c64bdeb2e877511632db8f   168     NaN     0.0
1    offer viewed  0009655768c64bdeb2e877511632db8f   192     NaN     0.0
2     transaction  0009655768c64bdeb2e877511632db8f   228   22.16     NaN
3  offer received  0009655768c64bdeb2e877511632db8f   336     NaN     0.0
4    offer viewed  0009655768c64bdeb2e877511632db8f   372     NaN     0.0

                           offer_id  difficulty  duration     offer_type  \
0  5a8bc65990b245e5a138643cd4eb9837           0         3  informational
1  5a8bc65990b245e5a138643cd4eb9837           0         3  informational
2  5a8bc65990b245e5a138643cd4eb9837           0         3  informational
3  3f207df678b143eea3cee63160fa8bed           0         4  informational
4  3f207df678b143eea3cee63160fa8bed           0         4  informational

   email  mobile  social  web
0      1       1       1    0
1      1       1       1    0
2      1       1       1    0
3      1       1       0    1
4      1       1       0    1
```

1.4 Finding successfull offers

1.4.1 Defining success

To train the proposed models, we need to define success. For this problem, it makes sense that sucess is when a user has completed the funnels mentioned above successfully.

Let's start by finding which users got to which steps of the funnel. For that, we'll separate the events in it's own tables adn create auxiliary columns. Then we'll join those datasets to come up with a single dataset that has the offer id, the person id, and three booleans for received, viewed and completed. We'll also include the considerations for the order of the performed events to be considered valid in this step.

[68]:
```python
def creating_event_df(original_df, event):
    '''
    this function takes in a dataframe that contains the 'event',
    'person' and 'time' columns and creates a new dataframe for only
    one selected event sorted by people and time.

    INPUT
    - original_df (df): dataframe that contains the 'event',
      'person' and 'time' columns
    - event (str): the target event

    OUTPUT
    - target_df (df): sorted dataframe with the desired filters
    '''
    target_df = original_df[original_df['event'] == event].copy()
    target_df.sort_values(['person', 'time'])

    return target_df
```

[69]:
```python
offer_received = creating_event_df(with_transaction, 'offer received')

offer_received.rename(columns = {'time': 'time_received'},
                      inplace = True)

offer_received = offer_received.drop(['event',
                                      'amount',
                                      'difficulty',
                                      'offer_type',
                                      'email',
                                      'mobile',
                                      'social',
                                      'web'],
                                     axis = 1)

offer_received['received'] = np.ones(len(offer_received))
```

[70]:
```python
offer_viewed = creating_event_df(with_transaction, 'offer viewed')

offer_viewed.rename(columns = {'time': 'time_viewed'},
                    inplace = True)

offer_viewed = offer_viewed.drop(['event',
                                  'amount',
                                  'reward',
                                  'duration',
                                  'difficulty',
                                  'offer_type',
```

```
                                         'email',
                                         'mobile',
                                         'social',
                                         'web'],
                                        axis = 1)

offer_viewed['viewed'] = np.ones(len(offer_viewed))
```

[71]:
```
offer_transaction = creating_event_df(with_transaction, 'transaction')

offer_transaction.rename(columns = {'time': 'time_transaction'},
                         inplace = True)

offer_transaction = offer_transaction.drop(['event',
                                            'reward',
                                            'duration',
                                            'difficulty',
                                            'offer_type',
                                            'email',
                                            'mobile',
                                            'social',
                                            'web'],
                                           axis = 1)

offer_transaction['has_transaction'] = np.ones(len(offer_transaction))
```

[72]:
```
offer_completed = creating_event_df(with_transaction, 'offer completed')

offer_completed.rename(columns = {'time': 'time_completed'},
                       inplace = True)

offer_completed = offer_completed.drop(['event',
                                        'amount',
                                        'reward',
                                        'duration',
                                        'difficulty',
                                        'offer_type',
                                        'email',
                                        'mobile',
                                        'social',
                                        'web'],
                                       axis = 1)

offer_completed['completed'] = np.ones(len(offer_completed))
```

[73]:
```
# merge event dataframes into one
offers_received_viewed = offer_received.merge(offer_viewed,
```

```
                                              how = 'left',
                                              on = ['person', 'offer_id'])

offers_received_viewed_transaction = offers_received_viewed.
 ↪merge(offer_transaction,
                                                                     how = 'left',
                                                                     on =␣
 ↪['person', 'offer_id'])

offers = offers_received_viewed_transaction.merge(offer_completed,
                                                  how = 'left',
                                                  on = ['person', 'offer_id'])

# reorder columns
offers = offers[['person',
                 'offer_id',
                 'received',
                 'viewed',
                 'has_transaction',
                 'completed',
                 'duration',
                 'time_received',
                 'time_viewed',
                 'time_transaction',
                 'time_completed',
                 'amount',
                 'reward']]

# add expiration time for the offer
offers['time_expiry'] = offers['duration'] + offers['time_received']
```

[74]:
```
# filter only pairs of events and person where the
# funnel order was followed correctly and the offer
# was successful
successful_offers = offers[(offers['has_transaction'] == 1) &                     ␣
 ↪        # the offer must have had a transaction
                           (offers['time_transaction'] >=␣
 ↪offers['time_viewed']) &      # the moment the transaction happened must be␣
 ↪after the offer was viewed
                           (offers['time_viewed'] >= offers['time_received']) &␣
 ↪        # the moment the offer was viewed must be after the offer was received
                           ((offers['time_expiry'] < offers['time_completed'])␣
 ↪|        # the offers must have been completed - either by transaction in the␣
 ↪case
```

```
                            (offers['time_expiry'] <␣
↪offers['time_transaction']))]      ## informational offers or by event -␣
↪before the expiration time

# add a column of ones signaling those are sucessful offers
successful_offers['is_successful'] = np.ones(len(successful_offers))
```

```
/home/julia.tessler/anaconda3/lib/python3.7/site-
packages/ipykernel_launcher.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  # This is added back by InteractiveShellApp.init_path()
```

[75]:
```
successful_offers.shape
```

[75]: (217659, 15)

[76]:
```
# filter only pairs of events and person where the
# funnel order was followed correctly but the offer
# was not successful
non_successful_offers = offers[offers['has_transaction'].isna()]      # if the␣
↪offer has no transaction, it wasn't successful

# add a column of ones signaling those are sucessful offers
non_successful_offers['is_successful'] = np.zeros(len(non_successful_offers))
```

```
/home/julia.tessler/anaconda3/lib/python3.7/site-
packages/ipykernel_launcher.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  import sys
```

[77]:
```
non_successful_offers.shape
```

[77]: (27573, 15)

Now we can merge it back into one dataset and then merge this data with the rest of the profile data.

[78]:
```
offers = successful_offers.merge(non_successful_offers,
                                 how = 'outer')
```

[79]:
```
offers.shape
```

[79]:
```
(245232, 15)
```

We also need to refine user data. Let's start by joining the `profile` data with the transactions.

[80]:
```
len(offers['person'].unique())
```

[80]:
```
16993
```

[81]:
```
len(processed_profile['id'].unique())
```

[81]:
```
17000
```

[82]:
```
len(with_transaction['person'].unique())
```

[82]:
```
17000
```

The amount of distinct users in our `offers` data isn't the same as it is in the `profile` data, which means there is a chance we have most of our offers covered by the `profile` data.

The `offers` dataset has 245,232 rows.

[83]:
```
selected_users_profile = offers['person'].isin(processed_profile['id'])
selected_users_offers = offers[selected_users_profile]
```

[84]:
```
selected_users = with_transaction['person'].
 ↪isin(selected_users_offers['person'])
selected_transactions = with_transaction[selected_users]
```

[85]:
```
selected_transactions = selected_transactions.drop(['event',
                                                    'time'], axis = 1)
```

[86]:
```
selected_transactions.shape
```

[86]:
```
(306508, 11)
```

Now we have to filter this dataset only for the successful or non-successful offers we found above.

[87]:
```
successful_transactions = offers.merge(selected_transactions,
                                       how = 'inner',
                                       right_on = ['person', 'offer_id'],
                                       left_on = ['person', 'offer_id'])
```

[88]:
```
successful_transactions.columns
```

[88]:
```
Index(['person', 'offer_id', 'received', 'viewed', 'has_transaction',
       'completed', 'duration_x', 'time_received', 'time_viewed',
```

```
       'time_transaction', 'time_completed', 'amount_x', 'reward_x',
       'time_expiry', 'is_successful', 'amount_y', 'reward_y', 'difficulty',
       'duration_y', 'offer_type', 'email', 'mobile', 'social', 'web'],
      dtype='object')
```

[89]:
```python
successful_transactions = successful_transactions.drop(['reward_x',
                                                        'received',
                                                        'viewed',
                                                        'has_transaction',
                                                        'completed',
                                                        'duration_x',
                                                        'time_received',
                                                        'time_viewed',
                                                        'time_transaction',
                                                        'time_completed',
                                                        'amount_x',
                                                        'time_expiry',
                                                       ],
                                                       axis = 1)

successful_transactions.rename(columns = {'reward_y': 'reward',
                                          'duration_y': 'duration',
                                          'amount_y': 'amount'},
                              inplace = True)
```

[90]:
```python
successful_transactions.shape
```

[90]:
```
(2472021, 12)
```

Now we have multiple lines for the same successful transaction. Let's leave only one line of informations for each person and offer pair.

[91]:
```python
successful_transactions = successful_transactions.drop_duplicates()
successful_transactions.head()
```

[91]:
```
                             person                          offer_id  \
0  0009655768c64bdeb2e877511632db8f  5a8bc65990b245e5a138643cd4eb9837
2  0009655768c64bdeb2e877511632db8f  5a8bc65990b245e5a138643cd4eb9837
3  0009655768c64bdeb2e877511632db8f  3f207df678b143eea3cee63160fa8bed
5  0009655768c64bdeb2e877511632db8f  3f207df678b143eea3cee63160fa8bed
6  0009655768c64bdeb2e877511632db8f  f19421c1d4aa40978ebb69ca19b0e20d

   is_successful  amount  reward  difficulty  duration     offer_type  email  \
0            1.0     NaN     0.0           0         3  informational      1
2            1.0   22.16     NaN           0         3  informational      1
3            1.0     NaN     0.0           0         4  informational      1
5            1.0    8.57     NaN           0         4  informational      1
```

```
6           1.0     NaN     5.0           5          5            bogo      1

   mobile  social  web
0       1       1    0
2       1       1    0
3       1       0    1
5       1       0    1
6       1       1    1
```

We still have some duplicates due to the multiple lines related to events... Since the `amount` column only happens when a user makes a transaction, this feature is highly important to predict the success because it's part of the definition of success. Therefore, it can't be used in the model and should be dropped.

[92]:
```
transactions_logs = successful_transactions.drop(['amount'], axis = 1)

transactions_logs = transactions_logs.dropna().drop_duplicates()
```

[93]:
```
transactions_logs.shape
```

[93]:
```
(62398, 11)
```

Now we can join the user data with the transaction logs.

[94]:
```
transactions_with_users = transactions_logs.merge(processed_profile,
                                                  how = 'left',
                                                  left_on = 'person',
                                                  right_on = 'id')
```

[95]:
```
transactions_with_users.columns
```

[95]:
```
Index(['person', 'offer_id', 'is_successful', 'reward', 'difficulty',
       'duration', 'offer_type', 'email', 'mobile', 'social', 'web', 'age',
       'gender', 'id', 'income', 'became_member_on_year'],
      dtype='object')
```

Cool! Now we're almost ready to start modelling. To model data, we need to remove the `person`/`id` and `offer_id` columns as well as encode the `offer_type` and `gender` (we'll use Scikit-learn's `LabelEncoder()` for this). The `amount` coly

[96]:
```
final_dataset = transactions_with_users.drop(['person',
                                              'offer_id',
                                              'id'],
                                             axis = 1)
```

[97]:
```
le = LabelEncoder()
```

[98]:
```
offer_types_list = list(final_dataset['offer_type'].unique())
types_encoder = le.fit(offer_types_list)
offer_type_encoded = le.transform(final_dataset['offer_type'])

final_dataset['offer_type_encoded'] = offer_type_encoded
```

[99]:
```
gender_list = list(final_dataset['gender'].unique())
gender_encoder = le.fit(gender_list)
gender_encoded = le.transform(final_dataset['gender'])

final_dataset['gender_encoded'] = gender_encoded
```

[100]:
```
final_dataset = final_dataset.drop(['offer_type',
                                    'gender'], axis = 1)
```

[101]:
```
final_dataset.columns
```

[101]:
```
Index(['is_successful', 'reward', 'difficulty', 'duration', 'email', 'mobile',
       'social', 'web', 'age', 'income', 'became_member_on_year',
       'offer_type_encoded', 'gender_encoded'],
      dtype='object')
```

[102]:
```
final_dataset.isna().sum()
```

[102]:
```
is_successful            0
reward                   0
difficulty               0
duration                 0
email                    0
mobile                   0
social                   0
web                      0
age                      0
income                   0
became_member_on_year    0
offer_type_encoded       0
gender_encoded           0
dtype: int64
```

[103]:
```
final_dataset.shape
```

[103]:
```
(62398, 13)
```

[104]:
```
final_dataset.head()
```

[104]:
```
   is_successful  reward  difficulty  duration  email  mobile  social  web  \
0            1.0     0.0           0         3      1       1       1    0
```

```
1             1.0     0.0           0         4      1        1        0     1
2             1.0     5.0           5         5      1        1        1     1
3             1.0     2.0          10        10      1        1        1     1
4             1.0     5.0           5         5      1        1        1     1

   age         income  became_member_on_year  offer_type_encoded  \
0   33   72000.000000                   2017                   2
1   33   72000.000000                   2017                   2
2   33   72000.000000                   2017                   0
3   33   72000.000000                   2017                   1
4  118   65404.991568                   2018                   0

   gender_encoded
0               1
1               1
2               1
3               1
4               3
```

1.5 Modeling

1.5.1 Separating data into train and test

We'll use Scikit-learn's `train_test_split` function to separate data, with 80% as train and 20% as test.

Our independent variables - or features - will be: * reward * difficulty * duration * email * mobile * social * web * amount * age * income * became_member_on_year * offer_type_encoded * gender_encoded

We'll train supervised models for this. Our dependent variable will be `is_successful`.

The supervised models that will be trained are: * Model 1: Logistic Regression * Model 2: Naïve Bayes * Model 3: Support Vector Machines (SVM) * Model 4: Decision Tree

We'll use Scikit-learn's framework for all models.

[105]:
```
features = final_dataset[['reward',
                          'difficulty',
                          'duration',
                          'email',
                          'mobile',
                          'social',
                          'web',
                          'age',
                          'income',
                          'became_member_on_year',
                          'offer_type_encoded',
                          'gender_encoded']]
```

```
y = final_dataset['is_successful']
```

[106]:
```
X_train, X_test, y_train, y_test = train_test_split(features,
                                                    y,
                                                    test_size = 0.8,
                                                    random_state = 42)
```

To train all models, we'll use Scikit-learn's `cross_val_score` with 5 folds.

1.5.2 Baseline model

As baseline model we'll use a naive one, given by Scikit-learn's `DummyClassifier`. The model shall predict by most frequent class. This is a great baseline model because it's no better than just saying that an offer will be a success just because that's the marjority's class (and, since this is an unbalanced problem, this means that predictions by the marjority will be better than flipping a fair coin to predict the class).

[107]:
```
dummy_clf = DummyClassifier(strategy = "most_frequent")

cross_val_baseline = cross_val_score(dummy_clf,
                                     X_train,
                                     y_train,
                                     cv = 5,
                                     scoring = 'f1_micro')
```

[108]:
```
cross_val_baseline.mean()
```

[108]: 0.6441221316975467

The baseline model has 64.41% of F1-Score. We're looking for models that can perform better than this one.

1.5.3 Model 1: Logistic Regression

The logistic regression is a fairly simple model that presents good results in robust datasets, such as this one. We expect it to be better than the baseline and, since this is one of the most explainable models there is, we might favor it depending on the results. The logistic regression (along with the Decision Tree) is one of the models with the easiest explanation we chose to train, which makes it a favourite to be te best model (but first let's see how the models perform).

Even though the logistic regression has analytical solution, Scikit-learn's implementation uses computational methods to solve it. Since this is a small dataset, we'll use the `liblinear` solver as suggested by the documentation.

[109]:
```
lr = LogisticRegression(solver = 'liblinear', random_state = 42)

cross_val_lr = cross_val_score(lr,
                               X_train,
                               y_train,
```

```
                              cv = 5,
                              scoring = 'f1_micro')
```

[110]:
```
cross_val_lr.mean()
```

[110]: 0.6662358493158751

We can see some marginal gain in the F1-Score: this model reached 66.62%.

1.5.4 Model 2: Naïve Bayes

We'll train a Gaussian Näive Bayes model. This model usually performs well in well defined classification models. The chosen classifier, Gaussian, assumes that the likelihood of the features comes from a Gaussian distribution (see documentation for more details).

Naïve Bayes classifiers use Bayesian statistics to find the parameter values. An advantage of Naïve Bayes is that it only requires a small number of training data to estimate the parameters necessary for classification, even though this is a naïve model, which makes it great for this problem. Also, it can perform very well for this type of problem, even when the data breaks the Gaussian assumption.

[111]:
```
nb = GaussianNB()

cross_val_nb = cross_val_score(nb,
                               X_train,
                               y_train,
                               cv = 5,
                               scoring = 'f1_micro')
```

[112]:
```
cross_val_nb.mean()
```

[112]: 0.702621055986057

This model performed a bit better than the Logistic Regression and baseline models when it comes to F1-Score: 70.26%.

1.5.5 Model 3: Support Vector Machines (SVM)

We'll train support vector machines. SVMs are considered more complex than the models above. We expect it to perform better than the baseline, buti it might start to overfit the model.

An SVM model builds a representation of the categories as points in space, mapped in a way that the categories are each divided by a clear gap that is as wide as possible (see more here. Also, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

For this problem, we'll use an SVC kernel, which is a linear one.

[113]:
```
sv = svm.SVC()

cross_val_sv = cross_val_score(sv,
```

```
                                X_train,
                                y_train,
                                cv = 5,
                                scoring = 'f1_micro')
```

```
/home/julia.tessler/anaconda3/lib/python3.7/site-
packages/sklearn/svm/base.py:193: FutureWarning: The default value of gamma will
change from 'auto' to 'scale' in version 0.22 to account better for unscaled
features. Set gamma explicitly to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
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  "avoid this warning.", FutureWarning)
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  "avoid this warning.", FutureWarning)
/home/julia.tessler/anaconda3/lib/python3.7/site-
packages/sklearn/svm/base.py:193: FutureWarning: The default value of gamma will
change from 'auto' to 'scale' in version 0.22 to account better for unscaled
features. Set gamma explicitly to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
```

[114]:
```
cross_val_sv.mean()
```

[114]:
```
0.6510127408915569
```

This model has 65.10% of F1-Score. It is better than the baseline model, but not better than the Naïve Bayes model.

1.5.6 Model 4: Decision Tree

We'll train a decision tree classifier. This is the most powerful of all the chosen models and is very likely to overfit.

Decision trees are highly explainable because they produce a flow-chart like structure as outcome, which means that we have a linear flow of decision making in order to classify the offers. It's a favourite to best model due to it's explainability (as mentioned above).

[115]:
```
dt = DecisionTreeClassifier(random_state = 42)

cross_val_dt = cross_val_score(dt,
                               X_train,
                               y_train,
                               cv = 5,
                               scoring = 'f1_micro')
```

[116]:
```
cross_val_dt.mean()
```

[116]:
```
0.6508533831240313
```

This better than the baseline model, since the F1-Score is 65.08%. But it's not the best. The Linear Regression model has better scores and it's explainable as well.

1.6 Choosing the best model

Based on the resuls we found above, the best model is the Naïve Bayes. Let's retrain it so we can keep it's coefficients and apply it to the test features.

[117]:
```
model = nb.fit(X_train, y_train)
```

[118]:
```
predictions = model.predict(X_test)
```

[119]:
```
# get the confusion matrix
pd.crosstab(y_test, predictions)
```

[119]:

col_0	0.0	1.0
is_successful		
0.0	6095	12012
1.0	3097	28715

[120]:
```
metrics.f1_score(y_test, predictions, average = 'micro')
```

[120]:
```
0.6973296740719966
```

[121]:
```
print(metrics.classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

         0.0       0.66      0.34      0.45     18107
         1.0       0.71      0.90      0.79     31812

    accuracy                           0.70     49919
   macro avg       0.68      0.62      0.62     49919
weighted avg       0.69      0.70      0.67     49919
```

The model performed not very well in the test dataset, reaching a 69.73% F1-Score. The decrease in the score was already expected, since this data is new to the model. But since this score is close to what we found during the train stage, this means that this model can be applied to other datapoints and still be trustworthy, as it'll produce similar results.

The other usual metrics performed fairly well, with exception of the recall for non-successful offers, which was 34% - meaning that it's prediction is worse than flipping a coin to predict the success of the offer.

Unfortunatelly, Naïve Bayes model do not have easy explanations for the coefficients, which means that we can't easily explain what variables are related to the success of the offer. What we can do is look into each variable and the associated probability to look into the relations.

[122]:
```
result_df = pd.DataFrame(X_train.columns)
result_df[['non successful', 'successful']] = pd.DataFrame(model.
↪predict_proba(X_train).tolist())

result_df
```

[122]:

	0	non successful	successful
0	reward	0.204731	0.795269
1	difficulty	0.925091	0.074909
2	duration	0.346706	0.653294
3	email	0.294267	0.705733
4	mobile	0.408526	0.591474
5	social	0.093768	0.906232
6	web	0.924745	0.075255
7	age	0.337013	0.662987
8	income	0.398634	0.601366
9	became_member_on_year	0.288445	0.711555
10	offer_type_encoded	0.118418	0.881582
11	gender_encoded	0.086060	0.913940

Also we can get the features that had the most predictive contribution to each class, but still no explainability.

[123]:
```
# source: https://stackoverflow.com/questions/50526898/
↪how-to-get-feature-importance-in-naive-bayes
# prints the top 10 most predictive features for the non-successful class
neg = model.theta_[0].argsort()
print(np.take(X_train.columns, neg[:10]))

print('')

# prints the top 10 most predictive features for the successful class
neg = model.sigma_[0].argsort()
print(np.take(X_train.columns, neg[:10]))
```

```
Index(['social', 'mobile', 'web', 'gender_encoded', 'offer_type_encoded',
```

```
       'email', 'reward', 'duration', 'difficulty', 'age'],
      dtype='object')

Index(['email', 'web', 'mobile', 'social', 'offer_type_encoded',
       'gender_encoded', 'became_member_on_year', 'duration', 'reward',
       'difficulty'],
      dtype='object')
```

If we consider the Logist Regression as the best explainable model, we can look into the coefficients to get the most important features.

[124]:
```
model_lr = lr.fit(X_train, y_train)
```

[125]:
```
predictions_lr = model_lr.predict(X_test)
```

[126]:
```
metrics.f1_score(y_test, predictions_lr, average = 'micro')
```

[126]:
```
0.6438029607964904
```

[127]:
```
# get the confusion matrix
pd.crosstab(y_test, predictions_lr)
```

[127]:

col_0	0.0	1.0
is_successful		
0.0	523	17584
1.0	197	31615

[128]:
```
# Logistic Regression needs a small transformation to get the right coefficients
transformed_coefficients = list(np.exp(model_lr.coef_))
cdf = pd.DataFrame(list(X_train.columns), transformed_coefficients).
 ↪reset_index()

cdf.columns = ['coefficient', 'feature']
print(cdf.sort_values(by = 'coefficient', ascending = False))
```

```
    coefficient                feature
0      1.051222                 reward
5      1.023997                 social
4      1.008203                 mobile
9      1.000550  became_member_on_year
3      1.000011                  email
8      0.999996                 income
11     0.999768         gender_encoded
7      0.998785                    age
6      0.995864                    web
2      0.992067               duration
10     0.987936     offer_type_encoded
1      0.960984             difficulty
```

The supervised models trained, with respective F1-Scores, were: * Baseline Model: Dummy Classifier for most frequent class * F1-Score: 64.41% * Model 1: Logistic Regression * F1-Score: 66.62% * Model 2: Naïve Bayes * F1-Score: 70.26% * Model 3: Support Vector Machines (SVM) * 65.10% * Model 4: Decision Tree * F1-Score: 65.08%

The best model was Naïve Bayes, but it has not explainability. The second best and explainable model was the Logistic Regression.

In order to have explainability, we loose predictive power: the F1-Score of the Logistic Regression model is 64.38%. But the value of the reward, followed by the offer sent by social networks. For the increase of one unit in each feature, we expect a increase of the respective coefficient in the success of the offer.

1.7 Conclusion and refinement

When we started, we wanted to make better purchasing offers to Starbucks' customers. For this, we used customer's past behaviour to find patterns and try to be more assertive. As given by the Udacity's Starbucks Project Overview, the basic task was to use the data to identify which groups of people are most responsive to each type of offer, and how best to present each type of offer. In other words, this is a classification problem where the model takes user behaviour data as input and produces a group as output (either previously defined or not).

For this project, we spent quite some time dealing with the features, manipulating tose to fit into the models. For that to happen, we found a way to define an offer success based on the user funnel performed from the transcript dataset.

Once we had the dataset, we trained 4 supervised learning models and a baseline one. The baseline was a incredibly naïve model that classified the items based on the most frequent class. The model with best performance was a Naïve Bayes. This model doesn't have easy explainability, which means we fail to find understainable patterns to provide offers. But this model achieved reasonable results when applied to the test dataset, meaning it can be applied to other datapoints and still produce the same level of results.

In order to get explainability, we chose the Logistic Regression model, that has lower predictive power. But with this model, we identified the top three most important features: reward, social and mobile.

Next steps would include better feature engineering and selection (we just used all features we could) and other classification models. The model selection should probably account for model explainability, which failed in this case. To make better decisions here, we could dive deeper into the post-mortem analysis of those models.

[ ]:

```

```