Machine Learning Engineer Nanodegree

Capstone Project - Starbucks Coffee Coupon

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I. Definition

Project Overview

The Dataset

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

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

Every offer has a validity period before the offer expires. As an example, a BOGO offer might be valid for only 5 days. 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.

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.

The Task

Your task is to combine `transaction` , `demographic` and `offer` data to determine which demographic groups (a.k.a what kind of consumers) respond best to which offer type.

Problem Statement

This is a supervised learning classification problem. Specifically, it is a `multi-label classification` problem.

- ##### Here is a brief description of the problem

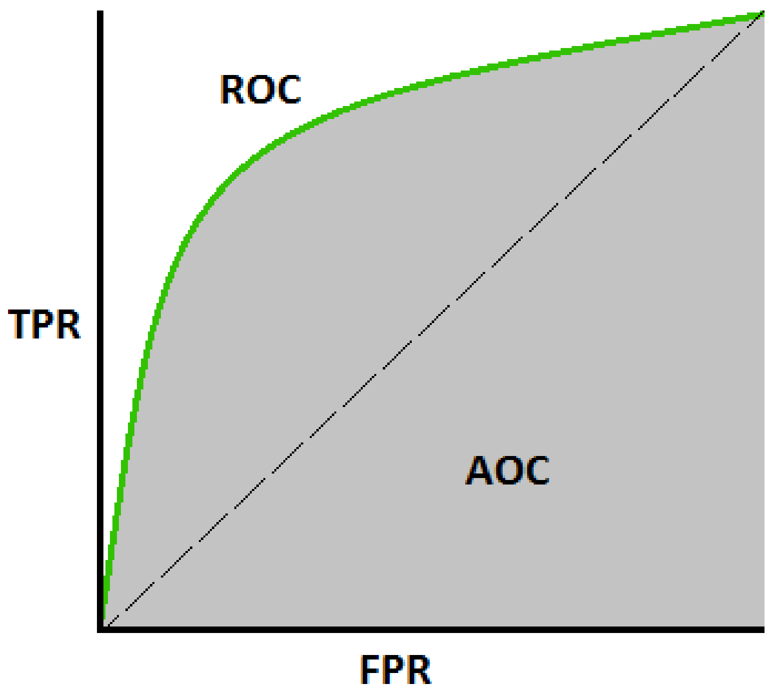
  - We have 8 different types of coupons(except for 2 informational coupon). For each consumer, during the given time period of 30 days, we know if a user has `successfully used a coupon`. Since a consumer can be given multiple coupon (these events are not exclusive to each other), it is a `multi-label binary classificatio` problem.
- ##### Definition of `successfuly used a coupon`:
  - The consumer has to view the coupon, and then within the effective duration of the coupon, complete it.

A successful model can predict how likely a consumer will use one of the 8 types of coupons, so that it helps Starbucks to send promotion to the target consumer, and, of course, capture to most value out of the person.

Metrics

ROC_AUC

Since it is a binary classfication problem, we will evaluate with `Area under the Curve (AUC) of Receiver Operating Characteristic (ROC)`

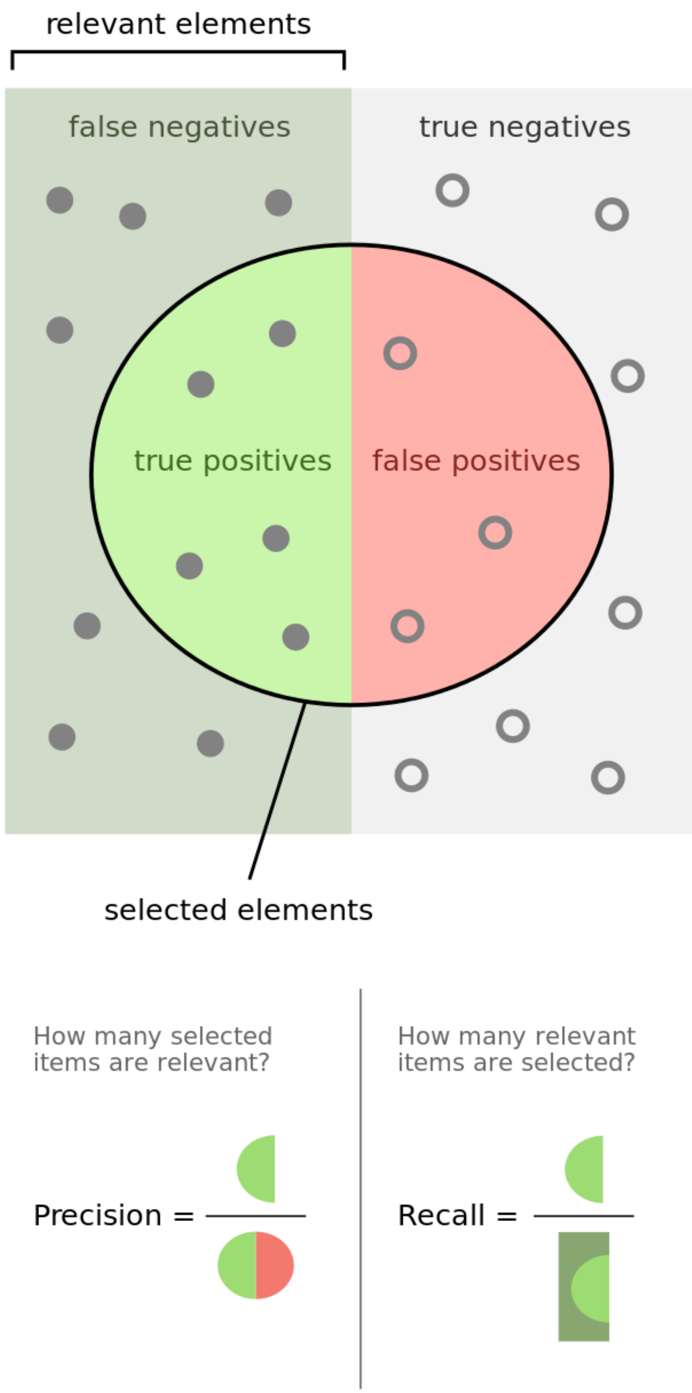


source:

[understanding-auc-roc-curve (https://towardsdatascience.com/understanding-auc-roc-curve-68b2303cc9c5)](https://towardsdatascience.com/understanding-auc-roc-curve-68b2303cc9c5)

Recall

We would rather give coupon to a consumer, even he / she won't use it, than missing a consumer that are potentially buying coffee. So recall is a more important measure than precision



source: [Recall definition from Wikipedia (https://en.wikipedia.org/wiki/Precision_and_recall)](https://en.wikipedia.org/wiki/Precision_and_recall)

Feature Importance

We will also run a `feature importance analysis` on the features. This can be done using `sklearn` -

II. Analysis

Data Exploration & Visualization

In [1]:
```
!python --version
```

```
Python 3.7.5
```

In [2]:
```
import pandas as pd
import numpy as np
import math
import json
import warnings

from helper.plot import plot_hist

warnings.filterwarnings('ignore')

# read in the json files
portfolio = pd.read_json('assets/portfolio.json', orient='records', line
s=True)
profile = pd.read_json('assets/profile.json', orient='records', lines=Tr
ue)
transcript = pd.read_json('assets/transcript.json', orient='records', li
nes=True)
```

Data Sets

Portfolio Data Exploration & Visualization

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)

In [3]:
```python
portfolio.set_index('id', inplace=True)
portfolio
```

Out[3]:

id	reward	channels	difficulty	duration	offer_type
ae264e3637204a6fb9bb56bc8210ddfd	10	[email, mobile, social]	10	7	bogo
4d5c57ea9a6940dd891ad53e9dbe8da0	10	[web, email, mobile, social]	10	5	bogo
3f207df678b143eea3cee63160fa8bed	0	[web, email, mobile]	0	4	informational
9b98b8c7a33c4b65b9aebfe6a799e6d9	5	[web, email, mobile]	5	7	bogo
0b1e1539f2cc45b7b9fa7c272da2e1d7	5	[web, email]	20	10	discount
2298d6c36e964ae4a3e7e9706d1fb8c2	3	[web, email, mobile, social]	7	7	discount
fafdcd668e3743c1bb461111dcafc2a4	2	[web, email, mobile, social]	10	10	discount
5a8bc65990b245e5a138643cd4eb9837	0	[email, mobile, social]	0	3	informational
f19421c1d4aa40978ebb69ca19b0e20d	5	[web, email, mobile, social]	5	5	bogo
2906b810c7d4411798c6938adc9daaa5	2	[web, email, mobile]	10	7	discount

Things that are interesting to us are:

- `difficulty` : how much do you need to spend to trigger the reward;
- `duration` : maximum time for the user to complete the offer;
- `offer_type` : Buy one get one free or just discount
- `channel & offer_type` : Since these information is catergorical, we would want to one-hot encode them, this will be the strategy for all other catergorical data

We know that there are 10 different offers, and `8` of them are actually coupons (we don't care about informational).

- Offer types are our `target data` . In the end, we want need a True / False (1 & 0) Table for each coupon map to each user

Consumer Profile Data Exploration & Visualization

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

In [4]:
```
profile.head(5)
```

Out[4]:

	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

There are some profile data that is invalid, let's see how many entry are there.

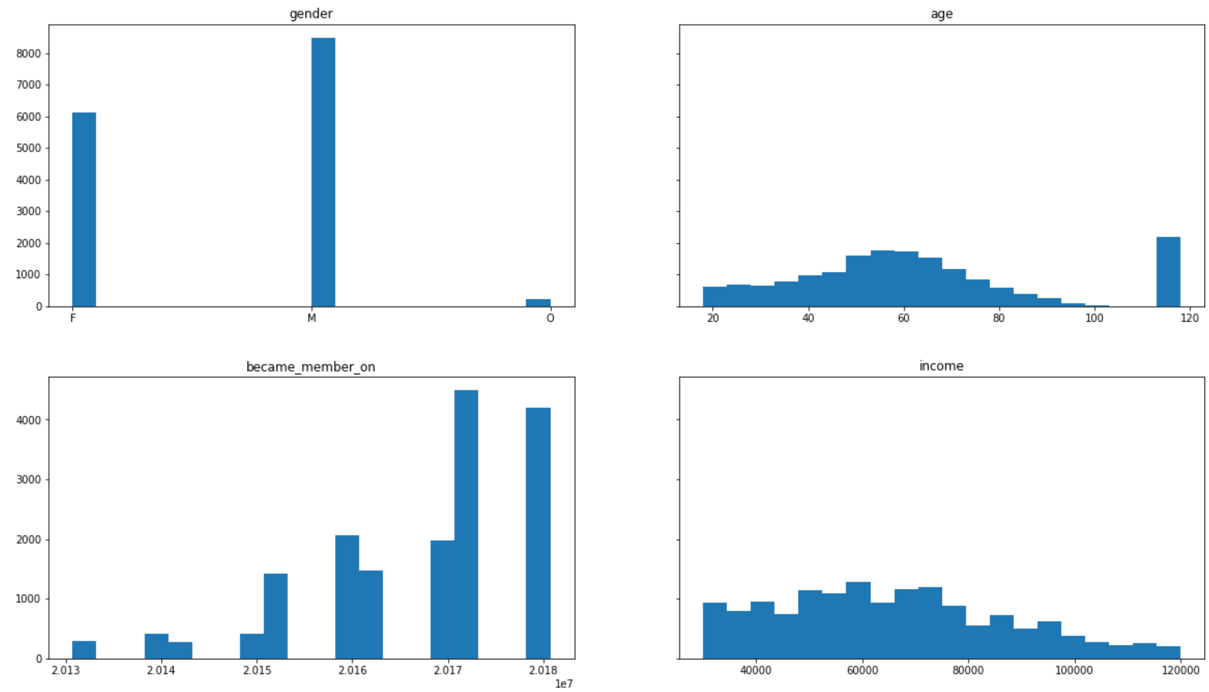
In [5]:
```
profile.set_index('id', inplace=True)
```

In [6]:
```
print(profile[profile['age'] == 118].shape)
print(profile[profile['income'].isnull()].shape)
print(profile[profile['gender'].isnull()].shape)
```

```
(2175, 4)
(2175, 4)
(2175, 4)
```

Histogram of profile

In [7]:
```
plot_hist(profile)
```



Transcript Data Exploration & Visualization

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

In [8]:
```
transcript.head()
```

Out[8]:

	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 [9]:
```
print(transcript.shape)
```

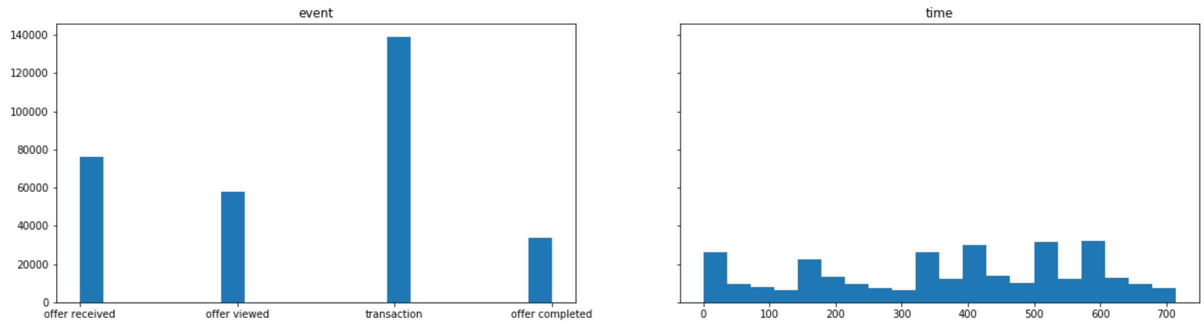
```
(306534, 4)
```

There are a lot of information we can gain from `transcript` dataframe

let's see what `event` type and `time` mean

Histogram of Transcript

In [10]:
```
plot_hist(transcript[['event', 'time']])
```



We can see there are 4 types of events.

- `offer received` : the event that the consumer received an offer, value is offer id(same for offer viewed ans completed)
- `offer viewed` : the event that the consumer received an offer, this is necessary for successfully complete an offer
- `offer completed` : the event that the consumer complete an offer, this is necessary for successfully complete an offer
- `transaction` : the event that the consumer make a purchase, value column shows the amount

In [11]:
```
transcript[transcript['event'] == 'offer received'].head()
```

Out[11]:

	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 [12]:
```python
transcript[transcript['event'] == 'offer viewed'].head()
```

Out[12]:

	person	event	value	time
12650	389bc3fa690240e798340f5a15918d5c	offer viewed	{'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}	0
12651	d1ede868e29245ea91818a903fec04c6	offer viewed	{'offer id': '5a8bc65990b245e5a138643cd4eb9837'}	0
12652	102e9454054946fda62242d2e176fdce	offer viewed	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}	0
12653	02c083884c7d45b39cc68e1314fec56c	offer viewed	{'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}	0
12655	be8a5d1981a2458d90b255ddc7e0d174	offer viewed	{'offer id': '5a8bc65990b245e5a138643cd4eb9837'}	0

In [13]:
```python
transcript[transcript['event'] == 'offer completed'].head()
```

Out[13]:

	person	event	value	tim
12658	9fa9ae8f57894cc9a3b8a9bbe0fc1b2f	offer completed	{'offer_id': '2906b810c7d4411798c6938adc9daaa5...	
12672	fe97aa22dd3e48c8b143116a8403dd52	offer completed	{'offer_id': 'fafdcd668e3743c1bb461111dcafc2a4...	
12679	629fc02d56414d91bca360decdfa9288	offer completed	{'offer_id': '9b98b8c7a33c4b65b9aebfe6a799e6d9...	
12692	676506bad68e4161b9bbaffeb039626b	offer completed	{'offer_id': 'ae264e3637204a6fb9bb56bc8210ddfd...	
12697	8f7dd3b2afe14c078eb4f6e6fe4ba97d	offer completed	{'offer_id': '4d5c57ea9a6940dd891ad53e9dbe8da0...	

In [14]:
```python
transcript[transcript['event'] == 'transaction'].head()
```

Out[14]:

	person	event	value	time
12654	02c083884c7d45b39cc68e1314fec56c	transaction	{'amount': 0.8300000000000001}	0
12657	9fa9ae8f57894cc9a3b8a9bbe0fc1b2f	transaction	{'amount': 34.56}	0
12659	54890f68699049c2a04d415abc25e717	transaction	{'amount': 13.23}	0
12670	b2f1cd155b864803ad8334cdf13c4bd2	transaction	{'amount': 19.51}	0
12671	fe97aa22dd3e48c8b143116a8403dd52	transaction	{'amount': 18.97}	0

Algorithms and Techniques

We will be using the following algorithms:

- Data Cleaning: clean and one hot encoding our dataframe
  - clean_portfolio
  - clean_profile
  - clean_transcript

- Data Creation: generate necessary data for training our model
  - generate_consumer_trend
    - based on the transcipts, organize consumer spending by day
  - generate_view_and_complete_day_df
    - based on the transcipts, organize consumer view and complete event by day
  - generate_target
    - based on consumer view and complete data, generate the valid complete target data
  - generate_coupon_sensitivity This is a complex algorithm to generate a feature called: coupon sensitivity, explained in the later section
    - get_days_not_affect_by_coupon
    - cal_avg_spend_without_coupon
    - generate_consumer_spending_couponx

Benchmark

Use `K-nearest neighbor` model as it is a fast and standard method for binary classification machine learning problems.

Reason for using KNN: It provides a quick way to train the model and test the result.

That being said, a quick and fairly accurate model will make it a good benchmark model.

3. Methodology

Data Pre-Processing

In [15]:
```
from helper.data_cleaning import clean_portfolio, clean_profile, clean_t
ranscript, generate_consumer_trend, \
generate_view_and_complete_day_df, generate_target, get_days_not_affect_
by_coupon, cal_avg_spend_without_coupon, \
generate_consumer_spending_couponx, generate_coupon_sensitivity
```

Portfolio

Perform the following steps to preprocess the data.

- Rename "id" to "offer_id"
- Drop "informational" offer type
- One Hot Encode `offer type` and `channels`

In [16]:
```
portfolio = clean_portfolio('assets/portfolio.json')
```

In [17]:
```
portfolio
```

Out[17]:

offer_id	reward	difficulty	duration	bogo	discount	email	mobile
ae264e3637204a6fb9bb56bc8210ddfd	10	10	7	1.0	0.0	1.0	1.0
4d5c57ea9a6940dd891ad53e9dbe8da0	10	10	5	1.0	0.0	1.0	1.0
9b98b8c7a33c4b65b9aebfe6a799e6d9	5	5	7	1.0	0.0	1.0	1.0
0b1e1539f2cc45b7b9fa7c272da2e1d7	5	20	10	0.0	1.0	1.0	0.0
2298d6c36e964ae4a3e7e9706d1fb8c2	3	7	7	0.0	1.0	1.0	1.0
fafdcd668e3743c1bb461111dcafc2a4	2	10	10	0.0	1.0	1.0	1.0
f19421c1d4aa40978ebb69ca19b0e20d	5	5	5	1.0	0.0	1.0	1.0
2906b810c7d4411798c6938adc9daaa5	2	10	7	0.0	1.0	1.0	1.0

Profile

Perform the following steps to clean and preprocess the data.

- Rename "id" to "consumer_id"
- Drop all `nan` data
- Drop "gender" that are in the `O` catergory
- Split date into `year` , `month` , `day`
- One Hot Encode `date` , `gender` , `age` and `income`

In [18]:
```
profile = clean_profile('assets/profile.json')
```

In [19]:
```
profile.head()
```

Out[19]:

	2013	2014	2015	2016	2017	2018	01	02	03	04	...
consumer_id											
0610b486422d4921ae7d2bf64640c50b	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...
78afa995795e4d85b5d9ceeca43f5fef	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...
e2127556f4f64592b11af22de27a7932	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	...
389bc3fa690240e798340f5a15918d5c	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	...
2eeac8d8feae4a8cad5a6af0499a211d	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...

5 rows × 40 columns

In [20]:
```
print(profile.shape)
```

```
(14613, 40)
```

Transaction

For transaction, first perform the following steps to clean and preprocess the data.

- rename `person` to `consumer_id`
- rename `value` to `offer_id` and reformat the value
- remove `{}` and `amount` , `offer_id` keys from the event column, keep only the values

In [21]:
```
transcript = clean_transcript('assets/transcript.json')
transcript
```

Out[21]:

	consumer_id	event	time	offer_ic
0	78afa995795e4d85b5d9ceeca43f5fef	offer received	0	9b98b8c7a33c4b65b9aebfe6a799e6d
1	a03223e636434f42ac4c3df47e8bac43	offer received	0	0b1e1539f2cc45b7b9fa7c272da2e1d
2	e2127556f4f64592b11af22de27a7932	offer received	0	2906b810c7d4411798c6938adc9daaa
3	8ec6ce2a7e7949b1bf142def7d0e0586	offer received	0	fafdcd668e3743c1bb461111dcafc2a
4	68617ca6246f4fbc85e91a2a49552598	offer received	0	4d5c57ea9a6940dd891ad53e9dbe8da
...	...	...	...	..
306529	b3a1272bc9904337b331bf348c3e8c17	transaction	714	1.5
306530	68213b08d99a4ae1b0dcb72aebd9aa35	transaction	714	9.5
306531	a00058cf10334a308c68e7631c529907	transaction	714	3.6
306532	76ddbd6576844afe811f1a3c0fbb5bec	transaction	714	3.5
306533	c02b10e8752c4d8e9b73f918558531f7	transaction	714	4.0

306534 rows × 4 columns

Then, we can generate two important dataframes.

- ##### 1. Target table
  - for each type of coupon, we can calculate if a consumer has successfully complete that offer. Thus we will have a True / False Table.
- ##### 2. Consumer Spending Trend
  - For each consumer, we can calculate the consumer's spending trend

In the following sections, I will discuss the implementation process

Implementation

1. Target table

How do we decide if a consumer `SUCCESSFULLY` used a coupon?

Here is the algorithm:

The consumer has to first `view` the coupon and then `complete` the coupon within the allowed time. We will use the `viewed` and `completed` information from the `transcript` table, then for each `viewed` , we calculate if the consumer `completed` the coupon within its duration.

Perform the following steps:

- Calculate a table on what day does the consumer viewed a specific coupon
- Calculate a table on what day does the consumer completed a specific coupon
- Based on these two table, caculate if the specific coupon is a valid completion, the definition of a valid completion: `day of completed - day of viewed < duration`

We will use the helper function `generate_view_and_complete_day_df` to do so. This function will take the transcript and return the a dataframe for every consumer's viewing activity each day, as well as a dataframe for offer completion.

We need these two dataframes to get the `valid completion` (target) dataframe

In [22]:
```
viewed_trend_day_df, completed_trend_day_df = generate_view_and_complete
_day_df(transcript)
```

In [23]:
```
print(viewed_trend_day_df.shape)
viewed_trend_day_df.head()
```

```
(16907, 30)
```

Out[23]:

	0	1
consumer_id		
5152fa6375184287b06e2fd0d5abed34	f19421c1d4aa40978ebb69ca19b0e20d	
5dca502de36e41f4b37c7f4795078b28	5a8bc65990b245e5a138643cd4eb9837	
6ccf170a9dc044b7947456417852bc43	f19421c1d4aa40978ebb69ca19b0e20d	
40b746a0008f476e92c356dd8a3ec666		ae264e3637204a6fb9bl
7d42182778104595bb6d5e920a767eca		

5 rows × 30 columns

In [24]:
```
print(completed_trend_day_df.shape)
completed_trend_day_df.head()
```

```
(16907, 30)
```

Out[24]:

	0	1	2	3	4	5	6	7
consumer_id								
5152fa6375184287b06e2fd0d5abed34	f19421c1d4aa40978ebb69ca19b0e20d							
5dca502de36e41f4b37c7f4795078b28								
6ccf170a9dc044b7947456417852bc43								
40b746a0008f476e92c356dd8a3ec666								22
7d42182778104595bb6d5e920a767eca								29

5 rows × 30 columns

Then we can use `generate_target` function to get the target data

In [25]:
```
target_coupon = generate_target(viewed_trend_day_df, completed_trend_day
_df, portfolio)
target_coupon
```

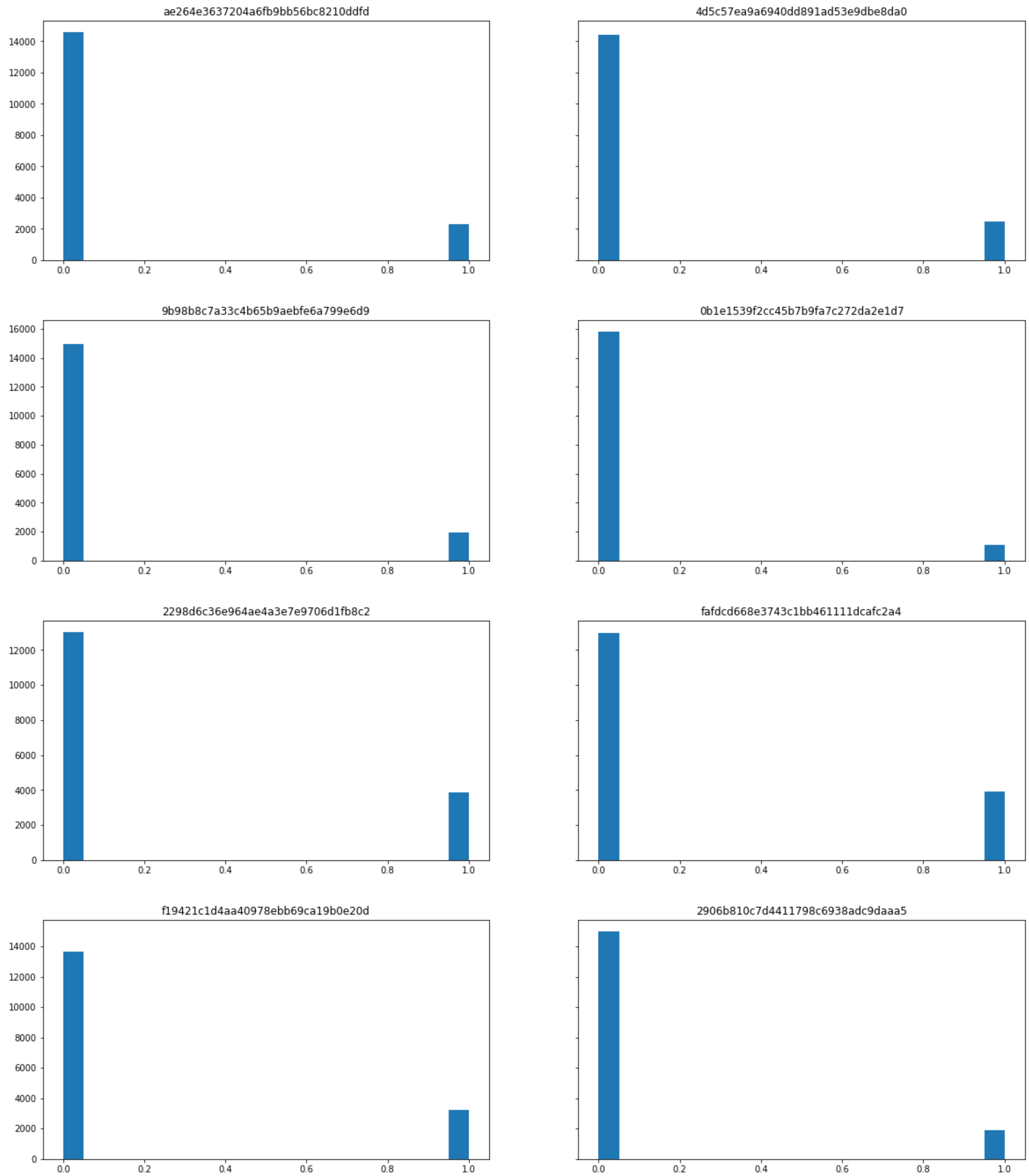
Out[25]:

	ae264e3637204a6fb9bb56bc8210ddfd	4d5c57ea9a6940dd891ad
consumer_id		
5152fa6375184287b06e2fd0d5abed34	0	
5dca502de36e41f4b37c7f4795078b28	0	
6ccf170a9dc044b7947456417852bc43	1	
40b746a0008f476e92c356dd8a3ec666	0	
7d42182778104595bb6d5e920a767eca	0	
...	...	
b84430e82831484aaa3642e41ada16d0	0	
1661d8802f16412b9bade2f1aea0e64e	1	
3fd0feaf8a5344d1a17be1707205814b	0	
83de7542018d455d9afa423626d7f5d3	1	
900e1382081b49b6ac7512fc02775d0f	0	

16907 rows × 8 columns

Let's take a quick look at how the data look like

In [26]:
```
plot_hist(target_coupon)
```



This distribution tells us the data is imbalanced, in the prediction model we need to address this

Now let's safe the target data to a `csv` file

In [27]:
```
target_coupon.to_csv('training_data/target.csv')
```

2. Consumer Spending Trend

We are now able to get all the transaction information. Based on this we can get the daily spending of each consumer

We use our helper function from the file `helper/data_cleaning.py` , `generate_consumer_trend` to do so, this function will take a transcript event from the `transcript` dataframe and organize it by time

In [28]:
```
consumer_trend_day_df = generate_consumer_trend(transcript)
```

In [29]:
```
consumer_trend_day_df.head()
```

Out[29]:

	0	1	2	3	4	5	6	7	8	9
consumer_id										
0009655768c64bdeb2e877511632db8f	0.0	0.00	0.00	0.00	0.0	0.00	0.00	0.0	0.0	22.16
00116118485d4dfda04fdbaba9a87b5c	0.0	0.00	0.00	0.00	0.0	0.00	0.00	0.0	0.0	0.00
0011e0d4e6b944f998e987f904e8c1e5	0.0	0.00	0.00	0.00	0.0	13.49	0.00	0.0	0.0	0.00
0020c2b971eb4e9188eac86d93036a77	0.0	0.00	49.63	24.39	0.0	0.00	24.31	0.0	0.0	0.00
0020ccbbb6d84e358d3414a3ff76cffd	0.0	16.27	0.00	0.00	0.0	0.00	0.00	0.0	0.0	11.65

5 rows × 30 columns

We now have the consumer trend of each day.

Save the consumer trend info to `consumer_trend_day.csv` for later use

In [30]:
```
consumer_trend_day_df.to_csv('assets/consumer_trend_day.csv')
```

Digging more into the spending trend

What can we gain from the trend?

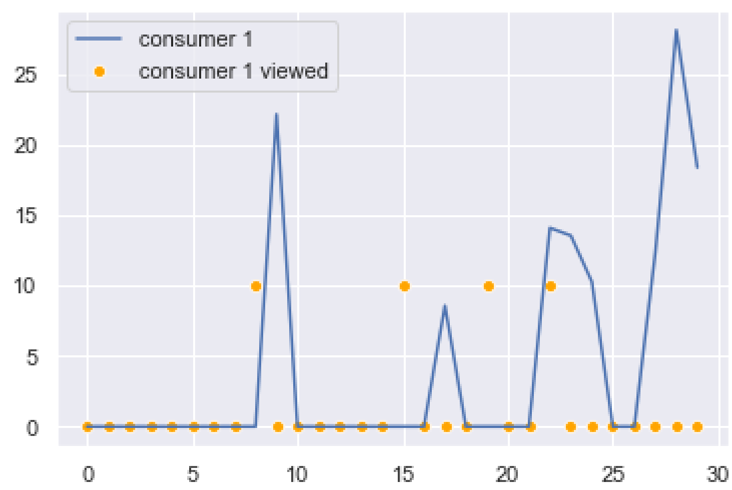
Let's take a close look at the spending trend of each consumer.

For example, let's plot the spending activity of consumer `0009655768c64bdeb2e877511632db8f` and consumer `0020ccbbb6d84e358d3414a3ff76cffd`

In [31]:
```
consumer_1 = consumer_trend_day_df.loc['0009655768c64bdeb2e877511632db8
f']
consumer_2 = consumer_trend_day_df.loc['0020ccbbb6d84e358d3414a3ff76cff
d']

consumer_1_viewed = list(viewed_trend_day_df.loc['0009655768c64bdeb2e877
511632db8f'])
for i, viewed in enumerate(consumer_1_viewed):
    if viewed =='':
        consumer_1_viewed[i] = 0
    else:
        consumer_1_viewed[i] = 10


consumer_2_viewed = list(viewed_trend_day_df.loc['0020ccbbb6d84e358d3414
a3ff76cffd'])
for i, viewed in enumerate(consumer_2_viewed):
    if viewed =='':
        consumer_2_viewed[i] = 0
    else:
        consumer_2_viewed[i] = 10
```

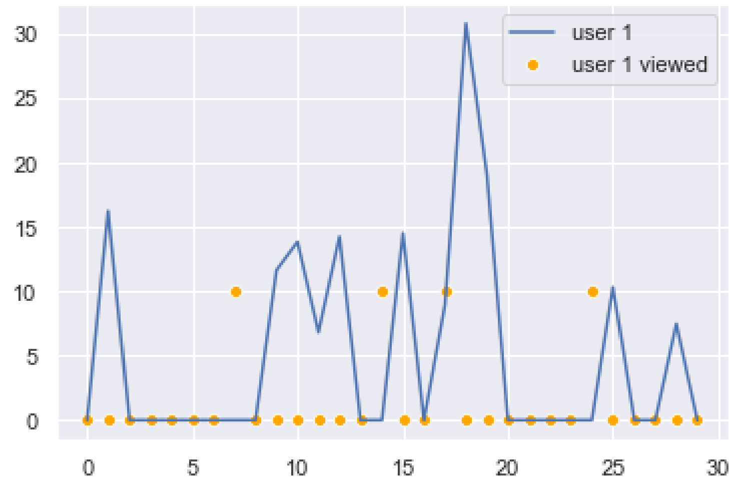
In [32]:
```
import seaborn as sns
sns.set()
import matplotlib.pyplot as plt

fig, ax = plt.subplots()
sns.scatterplot(consumer_1.index, consumer_1_viewed, ax=ax, label='consu
mer 1 viewed', color='orange')
sns.lineplot(consumer_1.index, consumer_1.values, ax=ax, label='consumer
1')
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x11e3e5e50>



In [33]:
```
fig, ax = plt.subplots()
sns.scatterplot(consumer_2.index, consumer_2_viewed, ax=ax, label='user
 1 viewed', color='orange')
sns.lineplot(consumer_2.index, consumer_2.values, ax=ax, label='user 1')
```

Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x11d1551d0>



An observation:

It seems like if there is a `coupon view` event, it is likely to have more spending right after it. The spending seems to be associate with `coupon view` , how do we describe this? Here is my suggestion:

Coupon Sensitivity

Based on this data visualization, we can tell the `view` activity has so what a connection to the spending activity:

For these 2 consumer, at least, it looks like `more spending activities are followed by the view acitivity`.

It will be helpful to create a feature to describe this phenomenon - `Coupon Sensitivity`

Here is how it works:

For the duration of the coupon (in the following days), how much `more` does this person spend compare to the purchase that are not initiated by the coupon - those purchases not in the following days of a coupon view event.

Formula for `coupon sensitivity`

```
(avg_couponx_effective_spend - avg_spend_without_coupon) / coupon_difficulty
```

- avg_couponx_effective_spend: if a consumer views a coupon, if he/she spend in the following days within its duration, these amount are called couponx_effective_spend, we then take the average.
- avg_spend_without_coupon: if a consumer spend on coffee in the days that are not affect by ANY coupon
- coupon difficulty: the difficulty of completing the coupon, this is to normalize each coupon

Follow the steps and we can get this feature:

1. Calculate all non affected by coupon days

In [34]:
```
days_not_affect_by_coupon = get_days_not_affect_by_coupon(viewed_trend_d
ay_df, portfolio)
```

In [35]:
```
days_not_affect_by_coupon
```

Out[35]:

	days_not_affect_by_coupon
consumer_id	
5152fa6375184287b06e2fd0d5abed34	[5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 27, 28, 29]
5dca502de36e41f4b37c7f4795078b28	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...
6ccf170a9dc044b7947456417852bc43	[5, 6, 26, 27, 28, 29]
40b746a0008f476e92c356dd8a3ec666	[0, 1, 15, 16, 24, 25, 26, 27, 28, 29]
7d42182778104595bb6d5e920a767eca	[0, 1, 2, 3, 4, 5, 6]
...	...
b84430e82831484aaa3642e41ada16d0	[0, 1, 2, 13, 14, 15, 16, 17, 18, 19, 20, 21, ...
1661d8802f16412b9bade2f1aea0e64e	[0, 1, 2, 3, 4, 5, 6, 21, 22, 23, 24]
3fd0feaf8a5344d1a17be1707205814b	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...
83de7542018d455d9afa423626d7f5d3	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...
900e1382081b49b6ac7512fc02775d0f	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13,...

16907 rows × 1 columns

Now we have a table of each consumer's days not affected by any coupon

2. Calculating each person's `avg_spend_without_coupon`

In [36]:
```
consumer_sensitivity = cal_avg_spend_without_coupon(consumer_trend_day_d
f, days_not_affect_by_coupon)
consumer_sensitivity
```

Out[36]:

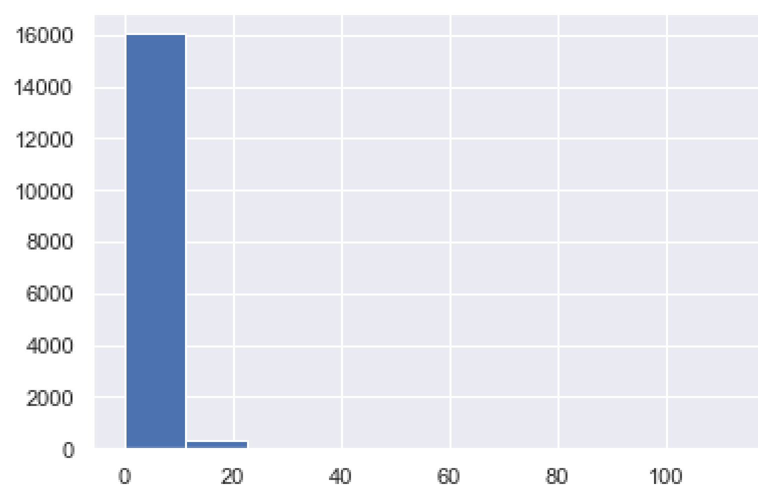
	avg_spend_without_coupon
consumer_id	
0009655768c64bdeb2e877511632db8f	6.237692
00116118485d4dfda04fdbaba9a87b5c	0.053846
0011e0d4e6b944f998e987f904e8c1e5	2.644615
0020c2b971eb4e9188eac86d93036a77	5.518462
0020ccbbb6d84e358d3414a3ff76cffd	4.158462
...	...
fff3ba4757bd42088c044ca26d73817a	5.186923
fff7576017104bcc8677a8d63322b5e1	1.100000
fff8957ea8b240a6b5e634b6ee8eafcf	0.000000
fffad4f4828548d1b5583907f2e9906b	2.246154
ffff82501cea40309d5fdd7edcca4a07	9.569231

16578 rows × 1 columns

A quick visualization:

In [37]:
```
consumer_sensitivity['avg_spend_without_coupon'].hist()
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x1377ee950>



Since the algorithm is rather complex, I wrap everything into the `generate_coupon_sensitivity` function, this is what it does:

- just like the way we calculate `avg_spend_without_coupon` , we calculate `avg_spending_affected by each coupon` , respectively
- We use the formular above, `(avg_couponx_effective_spend - avg_spend_without_coupon) / coupon_difficulty` , to calculate `coupon_sensitivity`

Below is the implementation, you can check out the helper file to see the details.

In [38]:
```
generate_coupon_sensitivity(consumer_sensitivity, viewed_trend_day_df, p
ortfolio, consumer_trend_day_df)
consumer_sensitivity = consumer_sensitivity[consumer_sensitivity.columns
[-8:]]
consumer_sensitivity
```

Out[38]:

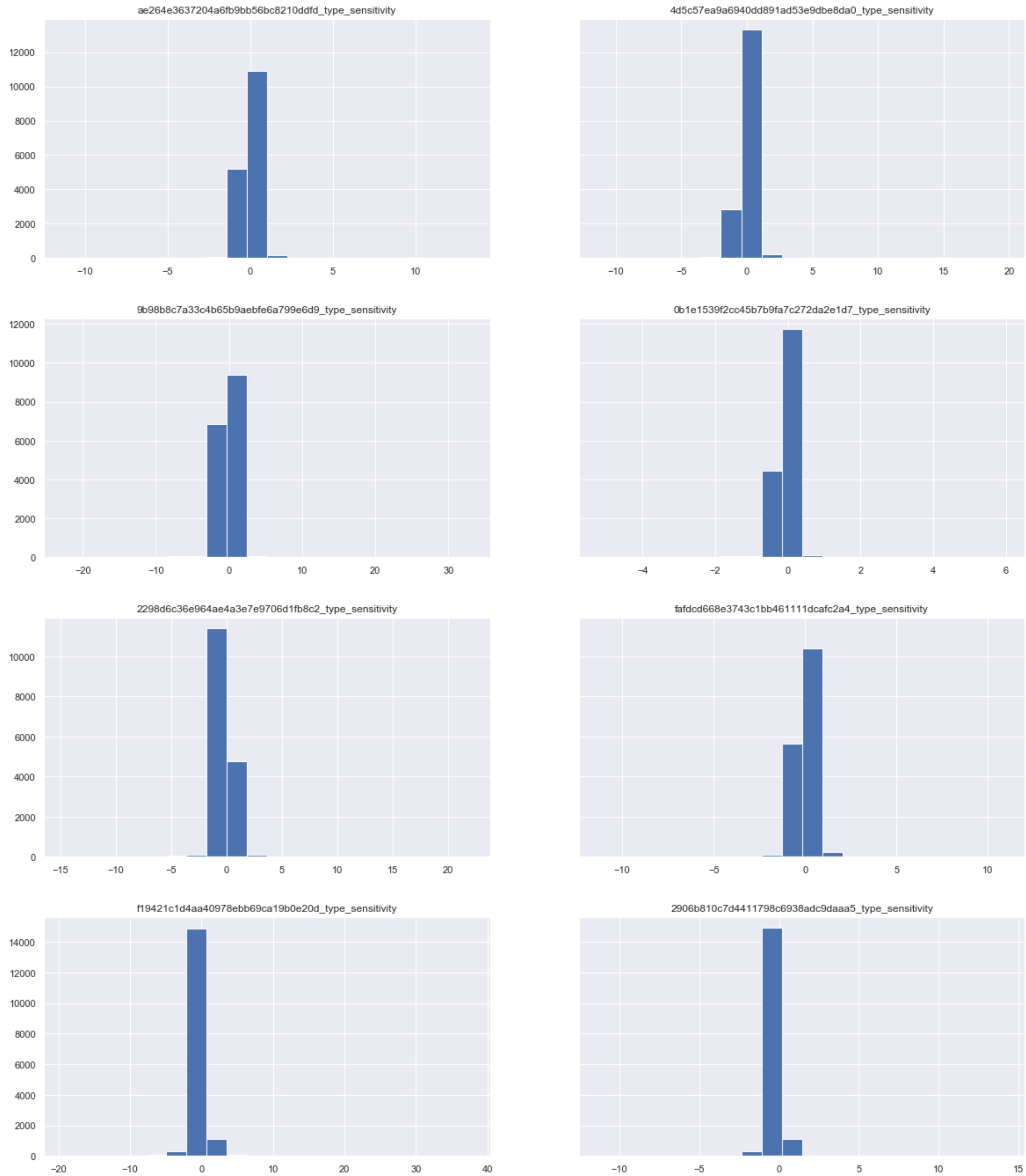
	ae264e3637204a6fb9bb56bc8210ddfd_type_sensitivity	4d5c57ea
consumer_id		
0009655768c64bdeb2e877511632db8f	-0.623769	
00116118485d4dfda04fdbaba9a87b5c	-0.005385	
0011e0d4e6b944f998e987f904e8c1e5	-0.264462	
0020c2b971eb4e9188eac86d93036a77	-0.551846	
0020ccbbb6d84e358d3414a3ff76cffd	-0.415846	
...	...	
fff3ba4757bd42088c044ca26d73817a	-0.518692	
fff7576017104bcc8677a8d63322b5e1	-0.080286	
fff8957ea8b240a6b5e634b6ee8eafcf	0.000000	
fffad4f4828548d1b5583907f2e9906b	-0.224615	
ffff82501cea40309d5fdd7edcca4a07	-0.956923	

16578 rows × 8 columns

Consumer Sensitivity Visualization

Let's plot the histogram of Consumer Sensitivity

In [39]:
```
plot_hist(consumer_sensitivity)
```



In [40]:
```
consumer_sensitivity.to_csv('training_data/consumer_sensitivity.csv')
```

Refinement

Now that we have the target information and coupon sensitivity, there is still room for improvement: We can get more features from the consumer trend information we generated.

Based on the trend, we are able to create more features we think may help the modeling

Consumer Trend Features

Create a table that contains the following features, these are some basic statistial features that we may be able to use

- Avg Daily spending: The mean of spending of each day
- Highest daily spending: The max of daily spending
- Lowest daily spending: The min of daily spending
- std_daily_spending: The standard deviation of daily spending
- Count days no spending: The number of days consumer did not spend on starbucks coffee
- count days spending 0_to_5: The number of days consumer spend 0 - 5 on starbucks coffee
- count days spending 5_to_10: The number of days consumer spend 5 - 10 on starbucks coffee
- count days spending 10_to_15: The number of days consumer spend 10 - 15 on starbucks coffee
- count days spending 15_to_20: The number of days consumer spend 15 - 20 on starbucks coffee
- count days spending 20_plus: The number of days consumer spend 20 plus on starbucks coffee

In [41]:
```
from helper.data_cleaning import generate_consumer_data
feature_group = generate_consumer_data(consumer_trend_day_df)
feature_group.head()
```

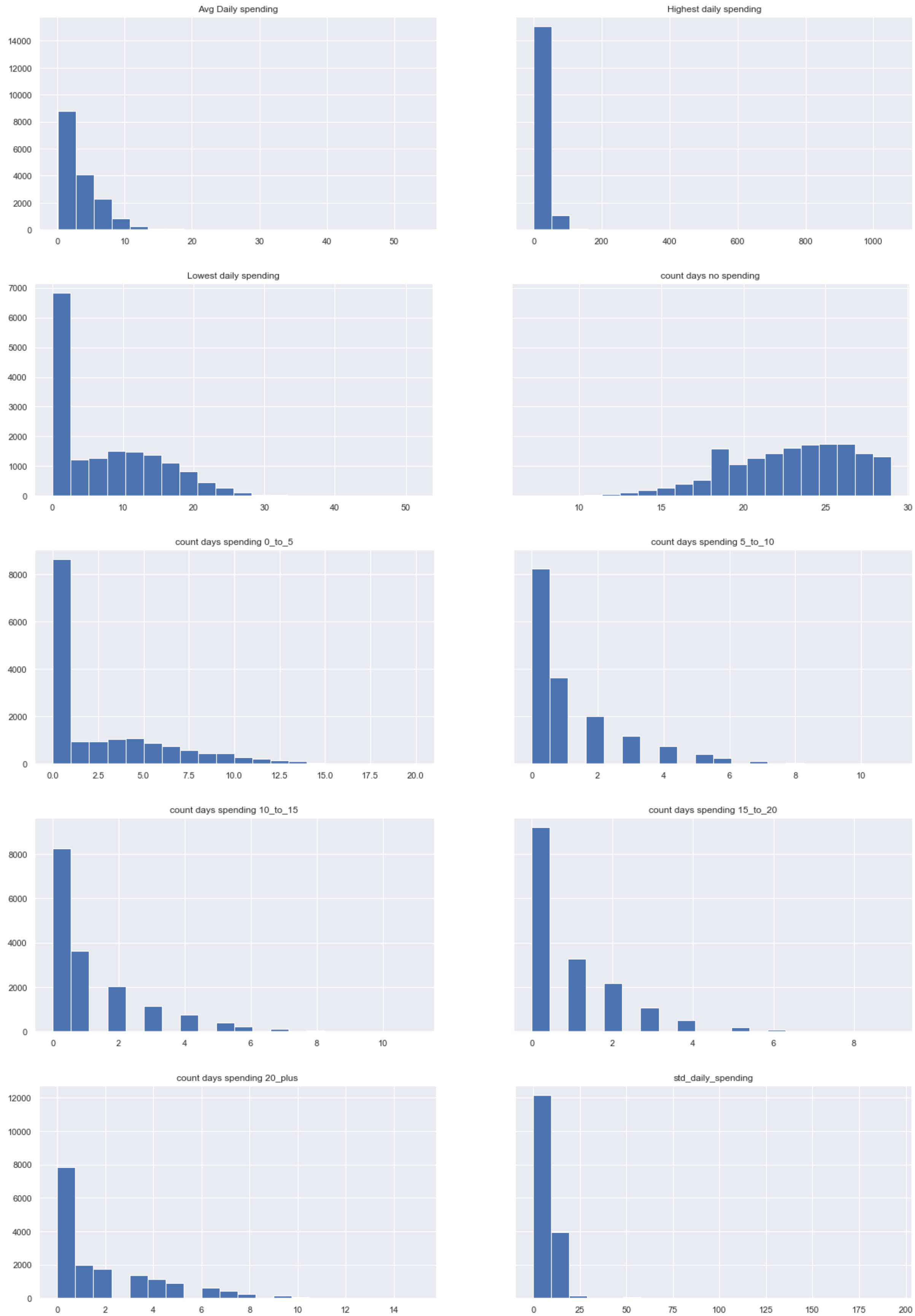
Out[41]:

consumer_id	Avg Daily spending	Highest daily spending	Lowest daily spending	count days no spending	count days spending 0_to_5	coun day spendin 5_to_1
0009655768c64bdeb2e877511632db8f	4.253333	28.16	8.57	22.0	0.0	1.
00116118485d4dfda04fdbaba9a87b5c	0.136333	3.39	0.70	28.0	2.0	0.
0011e0d4e6b944f998e987f904e8c1e5	2.648667	23.03	8.96	25.0	0.0	1.
0020c2b971eb4e9188eac86d93036a77	6.562000	49.63	17.24	24.0	0.0	0.
0020ccbbb6d84e358d3414a3ff76cffd	5.135000	30.84	6.81	19.0	0.0	3.

Feature Group Visualization

Let's plot the histogram of these data

In [42]:
```
plot_hist(feature_group)
```



In [43]:
```
feature_group.to_csv('training_data/consumer_features.csv')
```

In the following result section, we will join

-- portfolio

|

-- profile

|

-- consumer_sensitivity

|

-- feature_group

To become a dataframe that contains the target and the feature for each consumer / coupon relationship

4. Result

Model Evaluation and Validation

We will perform the following steps for our Training (evaluation metrix: with ROC_AUC / Recall / Accuracy):

1. Prepare the traing data, join all features and target into 1 dataframe
2. We will first run a KNN only based on all features
3. We apply random forest classifier on other target coupons and run a feature importance analysis on features, if necessary, we reduce the dimension using PCA
4. Improve with Hyper-parameter tuning (Optional)
5. Wrap the models to a single function that takes a consumer id and return the best coupon for this consumer

    - I will use the mathematic expectation, fomula:

      ```
      expectation = roc_auc * difficulty
      ```

      (the more difficult, the more that consumer will spend)

1. Prepare Training

We need to get the data that are from the dataset and from our previous analysis:

- `profile` , after running clean_profile function
- `portfolio` , after running clean_portfolio function
- `consumer_features` , where we created from our data analysis
- `consumer_sensitivity` , created from our visualization and analysis
- `target` from the target data we just created

In [46]:
```
consumer_feature = pd.read_csv('training_data/consumer_features.csv', in
dex_col='consumer_id')

consumer_sensitivity = pd.read_csv('training_data/consumer_sensitivity.c
sv', index_col='consumer_id')

target = pd.read_csv('training_data/target.csv', index_col='consumer_id'
)
```

In [47]:
```
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.metrics import roc_auc_score, accuracy_score, f1_score, pre
cision_score, recall_score
from sklearn.datasets import make_classification

from helper.data_cleaning import clean_profile, clean_portfolio, join_co
upon_profile_data, join_consumer_data
from helper.training import calc_coupon_x_consumer_data, run_predict_ran
dom_forest, run_predict_knn
```

Here is how we organize all the data:

for each coupon type in `target` , we join the target data and all features we just created correspond with the specific consumer using our helper function `calc_coupon_x_consumer_data` , for example:

In [48]:
```
# Calculate coupon 1 : ae264e3637204a6fb9bb56bc8210ddfd
coupon_0_consumer_data = calc_coupon_x_consumer_data(0, portfolio, profi
le, target, consumer_feature, consumer_sensitivity)
coupon_0_consumer_data
```

Out[48]:

	ae264e3637204a6fb9bb56bc8210ddfd	Avg Daily spending	Highest daily spending	L sp
consumer_id				
5152fa6375184287b06e2fd0d5abed34	0	5.415000	34.87	
5dca502de36e41f4b37c7f4795078b28	0	6.464667	39.94	
6ccf170a9dc044b7947456417852bc43	1	4.390667	25.19	
40b746a0008f476e92c356dd8a3ec666	0	3.949333	44.91	
7d42182778104595bb6d5e920a767eca	0	7.508667	49.41	
...	...	...	...	
b84430e82831484aaa3642e41ada16d0	0	1.881000	10.17	
1661d8802f16412b9bade2f1aea0e64e	1	6.287333	37.92	
3fd0feaf8a5344d1a17be1707205814b	0	3.642333	38.98	
83de7542018d455d9afa423626d7f5d3	1	8.107000	40.49	
900e1382081b49b6ac7512fc02775d0f	0	5.074667	45.41	

14219 rows × 68 columns

Now we have created a dataframe for traning coupon `ae264e3637204a6fb9bb56bc8210ddfd` , the 1st column is the target coupon, and all the other columns are features, we now have 14219 rows × 68 columns, which is a good size of features that we can train on.

2. Training on Benchmark Model

Let's run KNN classifier on our traning data, I am using KNN as it is one of the commonly used algorithm for this type of problem and it is fast. I have wrap the classifier in `run_predict_knn` function.

This function will take the index of the coupon, and join all features and target and run the prediction model, then print out the score for:

- `roc_auc`
- `accuracy`
- `recall`
- `precision`
- `f1 score`

In [49]:
```
for i in range(8):  # run though each coupon index
    run_predict_knn(i, portfolio, profile, target, consumer_feature, con
sumer_sensitivity)
```

```
coupon ae264e3637204a6fb9bb56bc8210ddfd
roc_auc score is 0.5581639753603946
accuracy score is 0.8316924519456165
recall score is 0.16261398176291794
precision score is 0.3905109489051095
f1 score is 0.2296137339055794
--------------------------------------------------------------
coupon 4d5c57ea9a6940dd891ad53e9dbe8da0
roc_auc score is 0.5693114728015563
accuracy score is 0.8173933427097984
recall score is 0.18641810918774968
precision score is 0.45454545454545453
f1 score is 0.26440037771482533
--------------------------------------------------------------
coupon 9b98b8c7a33c4b65b9aebfe6a799e6d9
roc_auc score is 0.5731637468934435
accuracy score is 0.873652133145804
recall score is 0.16230366492146597
precision score is 0.6118421052631579
f1 score is 0.25655172413793104
--------------------------------------------------------------
coupon 0b1e1539f2cc45b7b9fa7c272da2e1d7
roc_auc score is 0.5130452704154628
accuracy score is 0.9203000468823254
recall score is 0.03470031545741325
precision score is 0.24444444444444444
f1 score is 0.06077348066298343
--------------------------------------------------------------
coupon 2298d6c36e964ae4a3e7e9706d1fb8c2
roc_auc score is 0.6012215053238849
accuracy score is 0.7639474917955931
recall score is 0.2932405566600398
precision score is 0.49915397631133673
f1 score is 0.36944270507201005
--------------------------------------------------------------
coupon fafdcd668e3743c1bb461111dcafc2a4
roc_auc score is 0.5962873314571345
accuracy score is 0.7383966244725738
recall score is 0.3100558659217877
precision score is 0.4703389830508475
f1 score is 0.37373737373737376
--------------------------------------------------------------
coupon f19421c1d4aa40978ebb69ca19b0e20d
roc_auc score is 0.6503900944778974
accuracy score is 0.8387248007501172
recall score is 0.33029612756264237
precision score is 0.7435897435897436
f1 score is 0.45741324921135645
--------------------------------------------------------------
coupon 2906b810c7d4411798c6938adc9daaa5
roc_auc score is 0.5206341321875745
accuracy score is 0.8556024378809189
recall score is 0.06583629893238434
precision score is 0.2890625
f1 score is 0.1072463768115942
--------------------------------------------------------------
```

3. Random Forest Prediction & Feature Importance

The result is not satisfying. Let's perform a feature importance analysis and a random forest prediction.

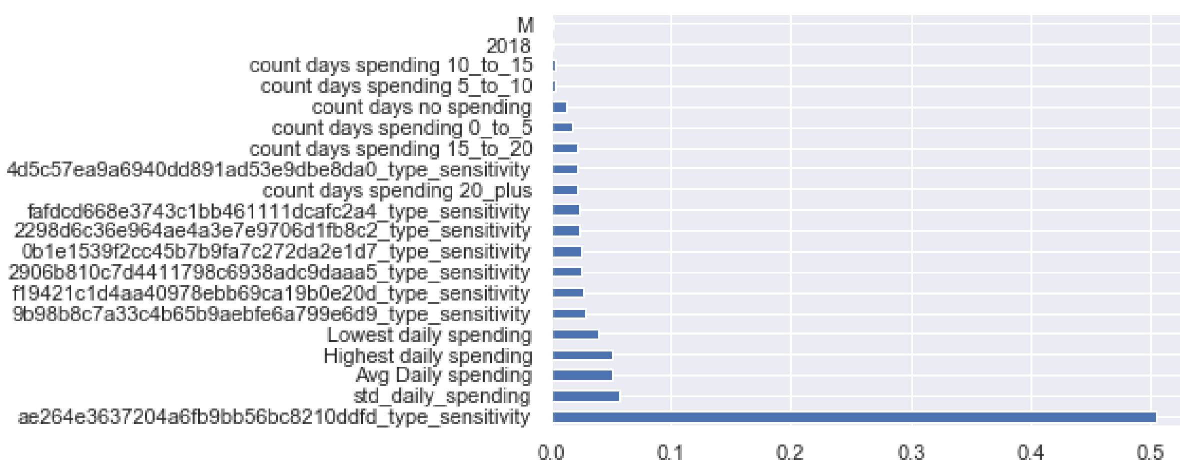
- First trial with coupon `ae264e3637204a6fb9bb56bc8210ddfd`

Execute run_predict_random_forest function. This function will take the index of the coupon, and join all features and target and run the prediction model, plot the feature importance (top 20 features) and evaluate our data then print out the score for:

- `roc_auc`
- `accuracy`
- `recall`
- `precision`
- `f1 score`

In [53]:
```
coupon_0_clf = run_predict_random_forest(0, portfolio, profile, target, consumer_feature, consumer_sensitivity)
```

```
coupon ae264e3637204a6fb9bb56bc8210ddfd
roc_auc score is 0.9245732212779437
accuracy score is 0.9491326769807783
recall score is 0.8890577507598785
precision score is 0.8024691358024691
f1 score is 0.843547224224946
--------------------------------------------------------------
```



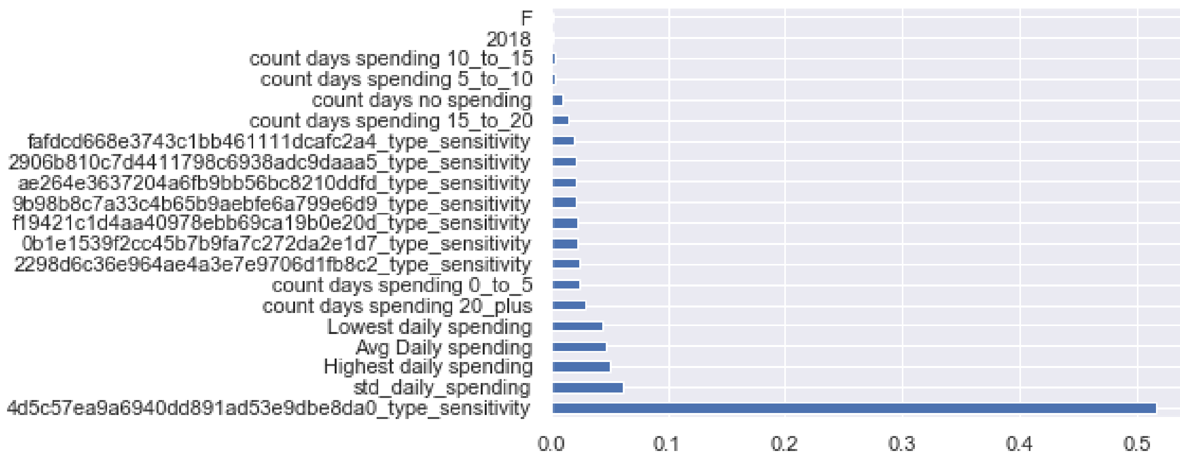
We have found out that `sensitivity` is a really important features, it is determistic to our model.

Because the multi-label classifier is rather harsh in sklearn, we will perform the same algorithm on each target coupon.

- coupon `4d5c57ea9a6940dd891ad53e9dbe8da0`

In [51]:
```
coupon_1_clf = run_predict_random_forest(1, portfolio, profile, target,
consumer_feature, consumer_sensitivity)
```

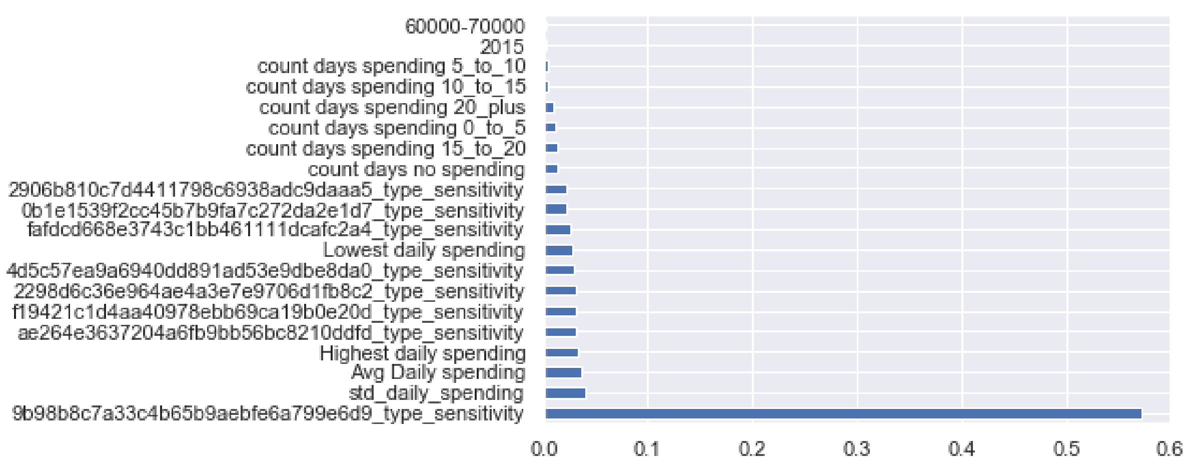
```
coupon 4d5c57ea9a6940dd891ad53e9dbe8da0
roc_auc score is 0.9309995397317563
accuracy score is 0.9535864978902954
recall score is 0.8961384820239681
precision score is 0.8486759142496847
f1 score is 0.8717616580310881
--------------------------------------------------------------
```



- coupon 9b98b8c7a33c4b65b9aebfe6a799e6d9

In [52]:
```
coupon_2_clf =run_predict_random_forest(2, portfolio, profile, target, c
onsumer_feature, consumer_sensitivity)
```

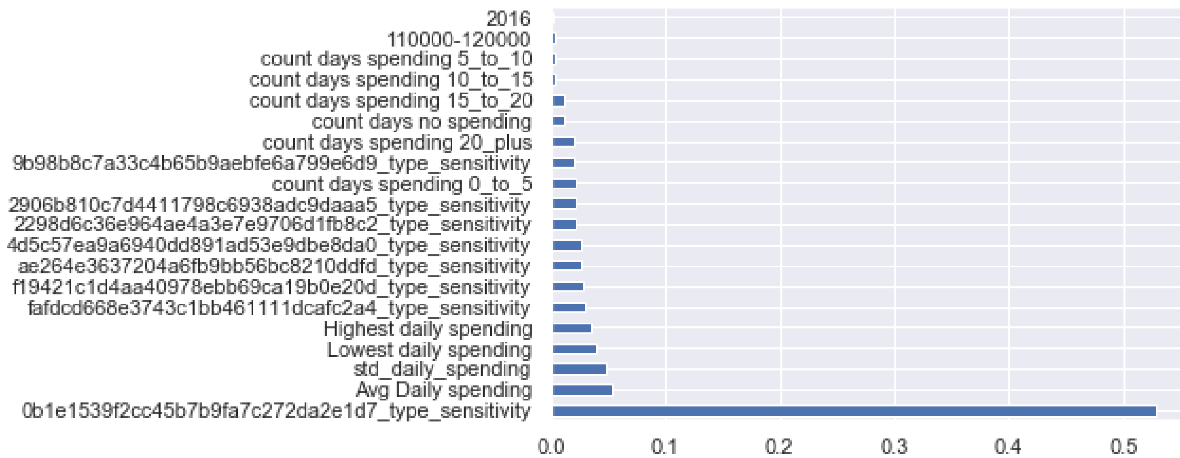
```
coupon 9b98b8c7a33c4b65b9aebfe6a799e6d9
roc_auc score is 0.9065580417458813
accuracy score is 0.9505391467416784
recall score is 0.8464223385689355
precision score is 0.7976973684210527
f1 score is 0.8213378492802709
--------------------------------------------------------------
```



- coupon 0b1e1539f2cc45b7b9fa7c272da2e1d7

In [54]:
```
coupon_3_clf = run_predict_random_forest(3, portfolio, profile, target,
consumer_feature, consumer_sensitivity)
```

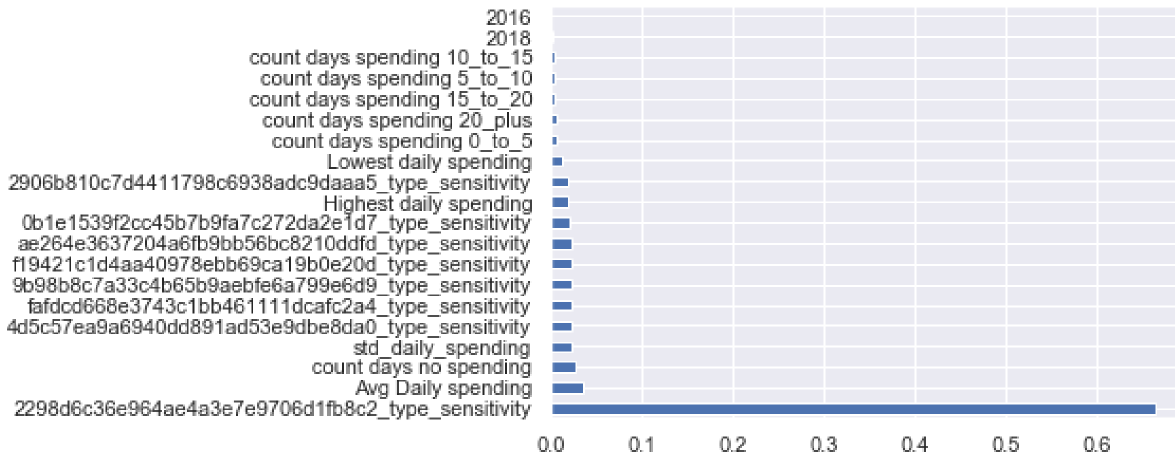
```
coupon 0b1e1539f2cc45b7b9fa7c272da2e1d7
roc_auc score is 0.9196418372099153
accuracy score is 0.96671354899203
recall score is 0.8643533123028391
precision score is 0.7345844504021448
f1 score is 0.7942028985507247
--------------------------------------------------------------
```



- coupon 2298d6c36e964ae4a3e7e9706d1fb8c2

In [55]:
```
coupon_4_clf = run_predict_random_forest(4, portfolio, profile, target,
consumer_feature, consumer_sensitivity)
```

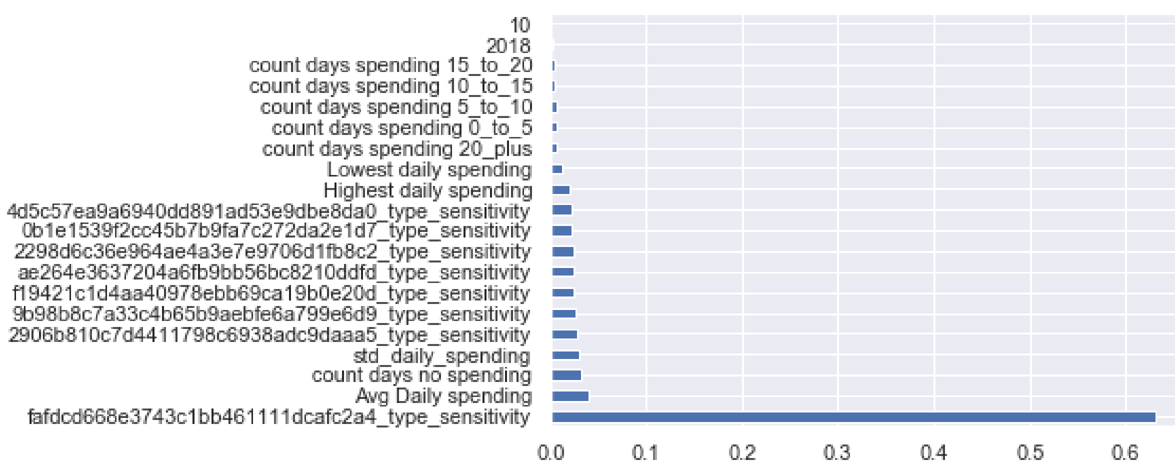
```
coupon 2298d6c36e964ae4a3e7e9706d1fb8c2
roc_auc score is 0.939115613070046
accuracy score is 0.9505391467416784
recall score is 0.9174950298210736
precision score is 0.8782112274024738
f1 score is 0.8974234321827905
---------------------------------------------------------------
```



- coupon fafdcd668e3743c1bb461111dcafc2a4

In [56]:
```
coupon_5_clf = run_predict_random_forest(5, portfolio, profile, target,
consumer_feature, consumer_sensitivity)
```

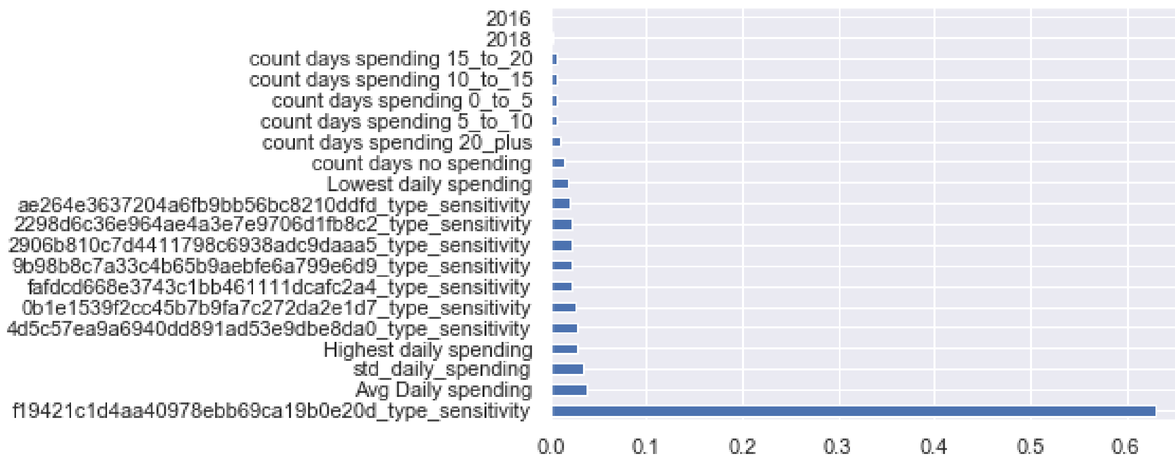
```
coupon fafdcd668e3743c1bb461111dcafc2a4
roc_auc score is 0.9426752985816497
accuracy score is 0.9479606188466948
recall score is 0.9320297951582868
precision score is 0.8704347826086957
f1 score is 0.900179856115108
---------------------------------------------------------------
```



- coupon `f19421c1d4aa40978ebb69ca19b0e20d`

In [57]:
```
coupon_6_clf = run_predict_random_forest(6, portfolio, profile, target,
consumer_feature, consumer_sensitivity)
```

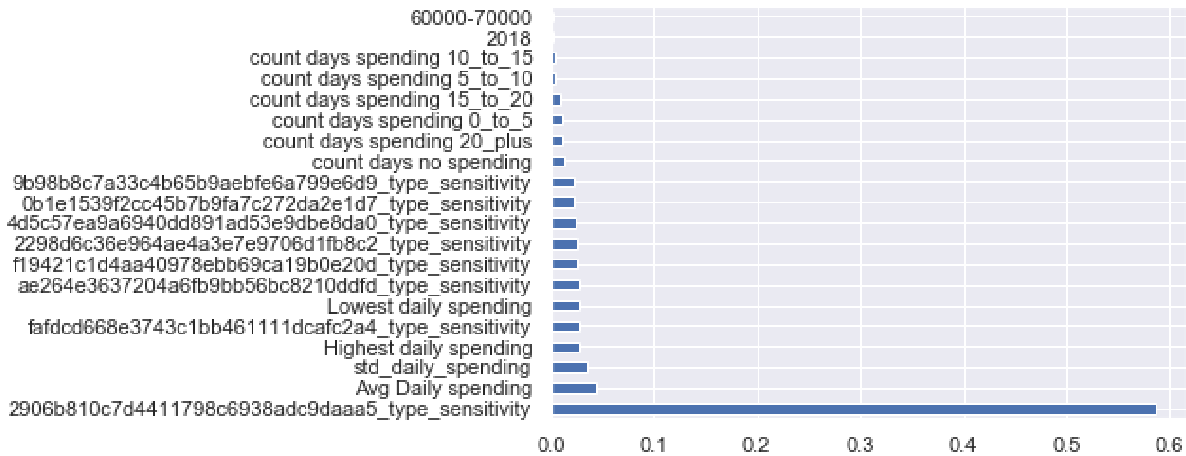
```
coupon f19421c1d4aa40978ebb69ca19b0e20d
roc_auc score is 0.9277699935185958
accuracy score is 0.9449132676980778
recall score is 0.8986332574031891
precision score is 0.8438502673796792
f1 score is 0.870380584666299
---------------------------------------------------------------
```



- coupon `2906b810c7d4411798c6938adc9daaa5`

In [59]:
```
coupon_7_clf = run_predict_random_forest(7, portfolio, profile, target,
consumer_feature, consumer_sensitivity)
```

```
coupon 2906b810c7d4411798c6938adc9daaa5
roc_auc score is 0.9367587603667864
accuracy score is 0.9622597280825129
recall score is 0.902135231316726
precision score is 0.8270799347471451
f1 score is 0.8629787234042554
--------------------------------------------------------------
```



All the results are looking good (roc_auc 90% +), I will skip the hyperopt and jump on to the final wrapping function.

5. Wrap the models to a single function that takes a consumer id and return the best coupon for this consumer

- This function will combine all the random forest classifiers, and then run prediction on a given consumer_id (new data), then make a prediction;
- If several classfiers returns true, it will take the one that has the highest mathematic expectation

In [60]:
```
def recommend_coupon_to_consumer(consumer_id):

    clf_list = [
        coupon_0_clf,
        coupon_1_clf,
        coupon_2_clf,
        coupon_3_clf,
        coupon_4_clf,
        coupon_5_clf,
        coupon_6_clf,
        coupon_7_clf
    ]

    expectations = []

    for clf in clf_list:

        pred = clf['clf'].predict(clf['consumer_data'].loc[[consumer_id
], clf['consumer_data'].columns[1:]])[0]
        difficulty = clf['consumer_data'].loc[consumer_id, 'difficulty']
        roc_auc = clf['roc_auc']

        expectations.append(pred * difficulty * roc_auc)

    max_i = 0
    max_e = expectations[max_i]

    for i, e in enumerate(expectations):
        if e > max_e:
            # update max_i and max_e
            max_i = i
            max_e = e

    best = clf_list[max_i]['consumer_data'].columns[0]
    print(f'best coupon for the consumer is: {best}, consumer expected s
pend is {max_e} ' )
    return best

recommend_coupon_to_consumer('0020ccbbb6d84e358d3414a3ff76cffd')
```

```
best coupon for the consumer is: 2298d6c36e964ae4a3e7e9706d1fb8c2, cons
umer expected spend is 6.573809291490322
```

Out[60]: `'2298d6c36e964ae4a3e7e9706d1fb8c2'`

Justification

Our model is way better than the benchmark, while the `KNN` model only have slightly better than `50%` of `roc_auc` , our models are `90%` + , average `30%` - `40%` better than the benchmark model. Same applies to `recall score` , `precision score` and `f1 score`

5. Conclusion

At this point, we are confident to say we have a good model to recommend a coupon for a consumer, as long as we have some historic data of this consumer.

Reflection

There are important learning that we can get from this project:

- Feature Engineering is the key: When you don't get good results, do not give up, there might be a way to interpret the data differently that can significantly improve the result (like `coupon_sensitivity` in this case, if we don't use it, the result would be a disaster)
- Visualization is helpful: Visualization can help you get a lot of insights, and lead you to the key features
- Ask the right question: One of the difficult part of this project is to ask the right question:
  - what is the target and how do you figure it out based on the original data? Once we know what is a meaningful problem to solve, we are half way to the solution

Improvement

- Hyper Parameter Tuning
  - We did not do any hyper parameter tuning on this project as the result is already good. But it definitely can improve the result even more
- Try CNNhe
  - Although we don't have tons of data entry, it would be a good method if we have more data from Starbucks
- Make An App
  - A next step to this project would be deploy this model to `sagemaker` and expose it as a `lambda function`. If Starbucks provide more data, we can keep updating the model and keep making it better