Starbucks Data Analysis Project

The problem that I chose to solve was to build a model that predicts whether a customer will respond to a Starbucks offer. The data set that I will be using for my analysis is 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. My 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. In the data set 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. I have extracted 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. I also kept in mind that someone using the app might make a purchase through the app without having received an offer or seen an offer. 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. Aim is to build a machine learning model that could help predicting which customer will actually use the offer.

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)-the type of offer ie BOGO, discount, informational. difficulty (int)-the minimum required to spend to complete an offer. reward (int)-the reward is given for completing an offer. duration (int)-time for the offer to be open, in days. channels (list of strings). # profile.json

age (int)-age of the customer. became_member_on (int)-the 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 the start of the test. The data begins at time t=0. value-(dict of strings)-either an offer id or transaction amount depending on the record.

Download dataset https://www.kaggle.com/blacktile/starbucks-app-customer-reward-program-data

In [9]:
```
import pandas as pd
import numpy as np
import math
import json
import matplotlib.pyplot as plt
import seaborn as sns

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

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

Out[5]:

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

In [6]:
```
profile.head()
```

Out[6]:

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

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

Out[7]:

	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

Cleaning the portfolio dataframe

In [8]:
```
# Changing the duration column values from days to hours
new_portfolio = portfolio.copy()
new_portfolio['duration'] = new_portfolio['duration'] * 24

# Applying one hot encoding to the channels column
new_portfolio['web'] = new_portfolio['channels'].apply(lambda x: 1 if 'web' in x else 0)
new_portfolio['email'] = new_portfolio['channels'].apply(lambda x: 1 if 'email' in x else 0)
new_portfolio['mobile'] = new_portfolio['channels'].apply(lambda x: 1 if 'mobile' in x else 0)
new_portfolio['social'] = new_portfolio['channels'].apply(lambda x: 1 if 'social' in x else 0)

# apply one hot encoding to offer_type column
offer_type = pd.get_dummies(new_portfolio['offer_type'])

# drop the channels and offer_type column
new_portfolio.drop(['channels'], axis=1, inplace=True)

# combine the portfolio and offer_type dataframe to form a cleaned dataframe
new_portfolio = pd.concat([new_portfolio, offer_type], axis=1, sort=False)

new_portfolio.head()
```

Out[8]:

	reward	difficulty	duration	offer_type	id	web	email	mobile	social	bogo	discount	informational
0	10	10	168	bogo	ae264e3637204a6fb9bb56bc8210ddfd	0	1	1	1	1	0	0
1	10	10	120	bogo	4d5c57ea9a6940dd891ad53e9dbe8da0	1	1	1	1	1	0	0
2	0	0	96	informational	3f207df678b143eea3cee63160fa8bed	1	1	1	0	0	0	1
3	5	5	168	bogo	9b98b8c7a33c4b65b9aebfe6a799e6d9	1	1	1	0	1	0	0
4	5	20	240	discount	0b1e1539f2cc45b7b9fa7c272da2e1d7	1	1	0	0	0	1	0

Cleaning the profile dataframe

In [9]:
```
#check for null values
profile.isnull().sum()
```

Out[9]:
```
gender              2175
age                    0
id                     0
became_member_on       0
income              2175
dtype: int64
```

In [10]:
```
profile[profile['age']== 118].age.count()
```

Out[10]: 2175

According to the description of the profile data frame and checking null values, it looks like values of gender & income are missing where age is 118. To confirm, I'll print the values with age 118.

In [11]:
```
profile[profile['age']== 118].drop(['became_member_on' ,'id'], axis=1)
```

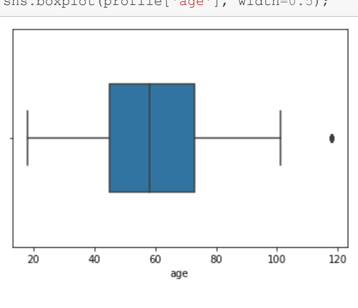
Out[11]:

	gender	age	income
0	None	118	NaN
2	None	118	NaN
4	None	118	NaN
6	None	118	NaN
7	None	118	NaN
...	...	...	...
16980	None	118	NaN
16982	None	118	NaN
16989	None	118	NaN
16991	None	118	NaN
16994	None	118	NaN

2175 rows × 3 columns

Thus, it is confirmed that both gender & income for the age 118 are missing. All missing age values are encoded as 118

In [12]:
```
sns.boxplot(profile['age'], width=0.5);
```



It seems to be like people with age greater than 80 don't use the app much or they may not drink much beverages. So, I consider people with the above age as outliers.

Merging the transcript and profile datasets

In [13]:
```
#merge the transcript and the profile datasets
df = transcript.merge(profile, left_on='person', right_on='id', how='outer')
df.head()
```

Out[13]:

	person	event	value	time	gender	age	id
0	78afa995795e4d85b5d9ceeca43f5fef	offer received	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	0	F	75	78afa995795e4d85b5d9ceeca43f5fe
1	78afa995795e4d85b5d9ceeca43f5fef	offer viewed	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}	6	F	75	78afa995795e4d85b5d9ceeca43f5fe
2	78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 19.89}	132	F	75	78afa995795e4d85b5d9ceeca43f5fe
3	78afa995795e4d85b5d9ceeca43f5fef	offer completed	{'offer_id': '9b98b8c7a33c4b65b9aebfe6a799e6d9...	132	F	75	78afa995795e4d85b5d9ceeca43f5fe
4	78afa995795e4d85b5d9ceeca43f5fef	transaction	{'amount': 17.78}	144	F	75	78afa995795e4d85b5d9ceeca43f5fe

In [14]:
```
null_profile = df[df['gender'].isnull()]
len(null_profile)
```

Out[14]: 33772

In [15]:
```
#null profile offer completion rate
null_rate = len(null_profile[null_profile['event']=='offer completed'])/len(null_profile[null_profile[
'event']=='offer received'])

print(null_rate)
```

0.11610065466448445

Now let us find out what is the offer completion rate for non null profiles.

In [16]:
```
not_null_profile=df[df['gender'].notnull()]
not_null_rate = len(not_null_profile[not_null_profile['event']=='offer completed'])/len(not_null_profil
e[not_null_profile['event']=='offer received'])

print(not_null_rate)
```

0.4878723628216117

The profiles which have null values in their profile have less offer completion rate so , I will be dropping the null values for my analysis.

In [17]:
```
#dropping null values
new_df = df[df['gender'].notnull()].copy()
new_df.drop('id', axis=1, inplace=True)
```

In [18]:
```
#changing became_member_on to the datetime format
new_df['became_member_on'] = pd.to_datetime(new_df['became_member_on'], format='%Y%m%d')

#creating a new column that has the year which customers became members
new_df['year'] = new_df['became_member_on'].apply(lambda x: str(x)[:4])

#changing the time in hours to days and also rounding up
new_df['days'] = new_df['time'].apply(lambda x: int(x / 24) + (x % 24 > 0))

#cleaning the value column
new_df['offer_id'] = new_df['value'].apply(lambda x: x['offer id'] if 'offer id' in x else x['offer_id'
] if 'offer_id' in x else np.nan)
new_df['amount'] = new_df['value'].apply(lambda x: x.get('amount', 0))
new_df.drop(['value'], axis=1, inplace=True)

new_df = new_df.reset_index(drop=True)
```

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

Out[19]:

	person	event	time	gender	age	became_member_on	income	year	days	
0	78afa995795e4d85b5d9ceeca43f5fef	offer received	0	F	75	2017-05-09	100000.0	2017	0	9b98b8c7a33c4b65b9aebfe6
1	78afa995795e4d85b5d9ceeca43f5fef	offer viewed	6	F	75	2017-05-09	100000.0	2017	1	9b98b8c7a33c4b65b9aebfe6
2	78afa995795e4d85b5d9ceeca43f5fef	transaction	132	F	75	2017-05-09	100000.0	2017	6	
3	78afa995795e4d85b5d9ceeca43f5fef	offer completed	132	F	75	2017-05-09	100000.0	2017	6	9b98b8c7a33c4b65b9aebfe6
4	78afa995795e4d85b5d9ceeca43f5fef	transaction	144	F	75	2017-05-09	100000.0	2017	6	

In [20]:
```
new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 272762 entries, 0 to 272761
Data columns (total 11 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   person            272762 non-null  object
 1   event             272762 non-null  object
 2   time              272762 non-null  int64
 3   gender            272762 non-null  object
 4   age               272762 non-null  int64
 5   became_member_on  272762 non-null  datetime64[ns]
 6   income            272762 non-null  float64
 7   year              272762 non-null  object
 8   days              272762 non-null  int64
 9   offer_id          148805 non-null  object
 10  amount            272762 non-null  float64
dtypes: datetime64[ns](1), float64(2), int64(3), object(5)
memory usage: 22.9+ MB
```

In [21]:
```
new_portfolio.head()
```

Out[21]:

	reward	difficulty	duration	offer_type	id	web	email	mobile	social	bogo	discount	informational
0	10	10	168	bogo	ae264e3637204a6fb9bb56bc8210ddfd	0	1	1	1	1	0	0
1	10	10	120	bogo	4d5c57ea9a6940dd891ad53e9dbe8da0	1	1	1	1	1	0	0
2	0	0	96	informational	3f207df678b143eea3cee63160fa8bed	1	1	1	0	0	0	1
3	5	5	168	bogo	9b98b8c7a33c4b65b9aebfe6a799e6d9	1	1	1	0	1	0	0
4	5	20	240	discount	0b1e1539f2cc45b7b9fa7c272da2e1d7	1	1	0	0	0	1	0

In [22]:
```
new_portfolio.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 12 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   reward         10 non-null     int64
 1   difficulty     10 non-null     int64
 2   duration       10 non-null     int64
 3   offer_type     10 non-null     object
 4   id             10 non-null     object
 5   web            10 non-null     int64
 6   email          10 non-null     int64
 7   mobile         10 non-null     int64
 8   social         10 non-null     int64
 9   bogo           10 non-null     uint8
 10  discount       10 non-null     uint8
 11  informational  10 non-null     uint8
dtypes: int64(7), object(2), uint8(3)
memory usage: 878.0+ bytes
```

In [23]:
```
full_df = new_df.merge(new_portfolio, left_on='offer_id', right_on='id', how='outer')
full_df.drop(['id'], axis=1, inplace=True)
```

In [24]:
```
full_df.head(20)
```

Out[24]:

	person	event	time	gender	age	became_member_on	income	year	days	
0	78afa995795e4d85b5d9ceeca43f5fef	offer received	0	F	75	2017-05-09	100000.0	2017	0	9b98b8c7a33c4b65b9aeb
1	78afa995795e4d85b5d9ceeca43f5fef	offer viewed	6	F	75	2017-05-09	100000.0	2017	1	9b98b8c7a33c4b65b9aeb
2	78afa995795e4d85b5d9ceeca43f5fef	offer completed	132	F	75	2017-05-09	100000.0	2017	6	9b98b8c7a33c4b65b9aeb
3	e2127556f4f64592b11af22de27a7932	offer received	408	M	68	2018-04-26	70000.0	2018	17	9b98b8c7a33c4b65b9aeb
4	e2127556f4f64592b11af22de27a7932	offer viewed	420	M	68	2018-04-26	70000.0	2018	18	9b98b8c7a33c4b65b9aeb
5	e2127556f4f64592b11af22de27a7932	offer completed	522	M	68	2018-04-26	70000.0	2018	22	9b98b8c7a33c4b65b9aeb
6	389bc3fa690240e798340f5a15918d5c	offer received	168	M	65	2018-02-09	53000.0	2018	7	9b98b8c7a33c4b65b9aeb
7	389bc3fa690240e798340f5a15918d5c	offer viewed	192	M	65	2018-02-09	53000.0	2018	8	9b98b8c7a33c4b65b9aeb
8	389bc3fa690240e798340f5a15918d5c	offer received	408	M	65	2018-02-09	53000.0	2018	17	9b98b8c7a33c4b65b9aeb
9	389bc3fa690240e798340f5a15918d5c	offer viewed	438	M	65	2018-02-09	53000.0	2018	19	9b98b8c7a33c4b65b9aeb
10	389bc3fa690240e798340f5a15918d5c	offer completed	498	M	65	2018-02-09	53000.0	2018	21	9b98b8c7a33c4b65b9aeb
11	d058f73bf8674a26a95227db098147b1	offer received	504	F	56	2018-04-28	88000.0	2018	21	9b98b8c7a33c4b65b9aeb
12	d058f73bf8674a26a95227db098147b1	offer viewed	522	F	56	2018-04-28	88000.0	2018	22	9b98b8c7a33c4b65b9aeb
13	d058f73bf8674a26a95227db098147b1	offer received	576	F	56	2018-04-28	88000.0	2018	24	9b98b8c7a33c4b65b9aeb
14	d058f73bf8674a26a95227db098147b1	offer viewed	606	F	56	2018-04-28	88000.0	2018	26	9b98b8c7a33c4b65b9aeb
15	ebe7ef46ea6f4963a7dd49f501b26779	offer received	0	M	59	2015-01-21	41000.0	2015	0	9b98b8c7a33c4b65b9aeb
16	ebe7ef46ea6f4963a7dd49f501b26779	offer received	576	M	59	2015-01-21	41000.0	2015	24	9b98b8c7a33c4b65b9aeb
17	ebe7ef46ea6f4963a7dd49f501b26779	offer viewed	714	M	59	2015-01-21	41000.0	2015	30	9b98b8c7a33c4b65b9aeb
18	868317b9be554cb18e50bc68484749a2	offer received	408	F	96	2017-11-17	89000.0	2017	17	9b98b8c7a33c4b65b9aeb
19	868317b9be554cb18e50bc68484749a2	offer completed	468	F	96	2017-11-17	89000.0	2017	20	9b98b8c7a33c4b65b9aeb

20 rows × 22 columns

In [25]:
```
#Let's see the orders of the variables
print( (full_df['event'].unique()), full_df['gender'].unique(), full_df['year'].unique())
```

```
['offer received' 'offer viewed' 'offer completed' 'transaction'] ['F' 'M' 'O'] ['2017' '2018' '2015'
'2016' '2014' '2013']
```

Turning categorical data to numbers

event - 0-'offer received'

1-'offer viewed'

2-'offer completed'

3-'transaction'

gender -

0-F

1-M

2-O

year -

0-'2013'

1-'2014'

2-'2015'

3-'2016'

4-'2017'

5-'2018'

offer_type

0-bogo

1-informational

2-discount

In [26]:
```
# Dataframe with old columns + additional columns that turned categorial variables into numbers.The num
bers only indicates different categories, not orders.
def cate2num(df, cols):
        for col in cols:
         #get all the unique categories in the column
         array = df[col].unique()

         #get the numbers of categories
         value_nums = len(array)

         #create new column
         df[col+'_id'] = df[col]

         for i in range(value_nums):
             #replace the variable with a number in the newly created column
             df[col+'_id'] = np.where(df[col]==array[i] , i, df[col+'_id'])

         return df
```

In [27]:
```
def clean_allcat(df, cols):

    cleaned_df = cate2num(df, cols)

    #years
    years = df['year'].unique()
    year_sorted = sorted([int(x) for x in list(years)])
    cleaned_df['year_id'] = df['year']
    for i in range(len(year_sorted)):
        cleaned_df['year_id'] = np.where(cleaned_df['year_id']==str(year_sorted[i]) , i, cleaned_df['ye
ar_id'])

    return cleaned_df
```

In [28]:
```
full_clean = clean_allcat(full_df, ['gender'])
full_clean = clean_allcat(full_clean, ['event'])
full_clean.head()
```

Out[28]:

	person	event	time	gender	age	became_member_on	income	year	days	
0	78afa995795e4d85b5d9ceeca43f5fef	offer received	0	F	75	2017-05-09	100000.0	2017	0	9b98b8c7a33c4b65b9aebfe6
1	78afa995795e4d85b5d9ceeca43f5fef	offer viewed	6	F	75	2017-05-09	100000.0	2017	1	9b98b8c7a33c4b65b9aebfe6
2	78afa995795e4d85b5d9ceeca43f5fef	offer completed	132	F	75	2017-05-09	100000.0	2017	6	9b98b8c7a33c4b65b9aebfe6
3	e2127556f4f64592b11af22de27a7932	offer received	408	M	68	2018-04-26	70000.0	2018	17	9b98b8c7a33c4b65b9aebfe6
4	e2127556f4f64592b11af22de27a7932	offer viewed	420	M	68	2018-04-26	70000.0	2018	18	9b98b8c7a33c4b65b9aebfe6

5 rows × 25 columns

In [29]:
```
full_clean['interacted'] = 1
person_all_offers = full_clean.groupby(['person', 'offer_id','event'])['interacted'].max().unstack(fill
_value=0)

#if a person (did not use an offer) or (used it without viewing), then the offer is wasted
person_all_offers['wasted'] = np.where((person_all_offers["offer completed"]==1)&(person_all_offers["of
fer viewed"]==1), 0, 1)
person_all_offers
```

Out[29]:

person	offer_id	offer completed	offer received	offer viewed	wasted
0009655768c64bdeb2e877511632db8f	2906b810c7d4411798c6938adc9daaa5	1	1	0	1
	3f207df678b143eea3cee63160fa8bed	0	1	1	1
	5a8bc65990b245e5a138643cd4eb9837	0	1	1	1
	f19421c1d4aa40978ebb69ca19b0e20d	1	1	1	0
	fafdcd668e3743c1bb461111dcafc2a4	1	1	1	0
...	...	...	...	...	...
fffad4f4828548d1b5583907f2e9906b	f19421c1d4aa40978ebb69ca19b0e20d	1	1	1	0
ffff82501cea40309d5fdd7edcca4a07	0b1e1539f2cc45b7b9fa7c272da2e1d7	1	1	1	0
	2906b810c7d4411798c6938adc9daaa5	1	1	1	0
	9b98b8c7a33c4b65b9aebfe6a799e6d9	1	1	1	0
	fafdcd668e3743c1bb461111dcafc2a4	1	1	1	0

55222 rows × 4 columns

In [30]:
```
#creating a new dataframe with only the information that we need to build the model
model_df = person_all_offers['wasted']
model_df.reset_index(level=['person', 'offer_id'])
model_df= model_df.to_frame().reset_index()
model_df.head()
```

Out[30]:

	person	offer_id	wasted
0	0009655768c64bdeb2e877511632db8f	2906b810c7d4411798c6938adc9daaa5	1
1	0009655768c64bdeb2e877511632db8f	3f207df678b143eea3cee63160fa8bed	1
2	0009655768c64bdeb2e877511632db8f	5a8bc65990b245e5a138643cd4eb9837	1
3	0009655768c64bdeb2e877511632db8f	f19421c1d4aa40978ebb69ca19b0e20d	0
4	0009655768c64bdeb2e877511632db8f	fafdcd668e3743c1bb461111dcafc2a4	0

In [31]:
```
df=pd.merge(model_df, full_clean, how='inner', sort=True)
```

In [32]:
```
df = clean_allcat(df, [ 'offer_type'])
df = clean_allcat(df, [ 'offer_id'])
df.drop(['gender', 'offer_type', 'offer_id', 'year','event','time','became_member_on','year','days','am
ount','interacted'], axis=1, inplace=True)
```

In [33]:
```
df.head()
```

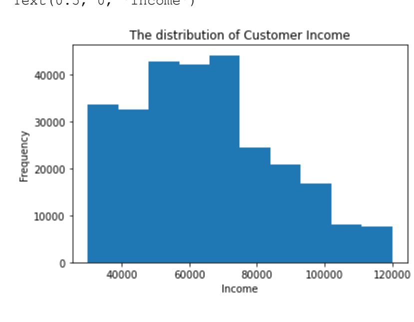
Out[33]:

	person	wasted	age	income	reward	difficulty	duration	web	email	mobile	social	bogo	discount	inf
0	0009655768c64bdeb2e877511632db8f	1	33	72000.0	2.0	10.0	168.0	1.0	1.0	1.0	0.0	0.0	1.0	
1	0009655768c64bdeb2e877511632db8f	1	33	72000.0	2.0	10.0	168.0	1.0	1.0	1.0	0.0	0.0	1.0	
2	0009655768c64bdeb2e877511632db8f	1	33	72000.0	0.0	0.0	96.0	1.0	1.0	1.0	0.0	0.0	0.0	
3	0009655768c64bdeb2e877511632db8f	1	33	72000.0	0.0	0.0	96.0	1.0	1.0	1.0	0.0	0.0	0.0	
4	0009655768c64bdeb2e877511632db8f	1	33	72000.0	0.0	0.0	72.0	0.0	1.0	1.0	1.0	0.0	0.0	

EDA

In [34]:
```
cust_income = full_clean['income'].plot(kind='hist', bins=10, title='The distribution of Customer Incom
e')
cust_income.set_xlabel("Income")
```

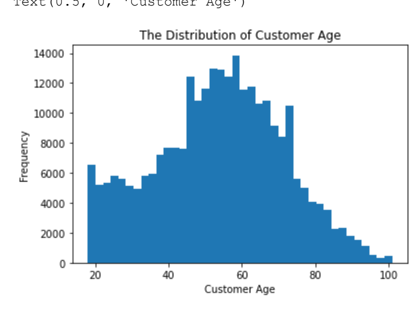
Out[34]: Text(0.5, 0, 'Income')



Max number of Customers have income ranging between 50000-70000.

In [35]:
```
cust_age = full_clean['age'].plot(kind='hist', bins=40, title='The Distribution of Customer Age')
cust_age.set_xlabel("Customer Age")
```

Out[35]: Text(0.5, 0, 'Customer Age')



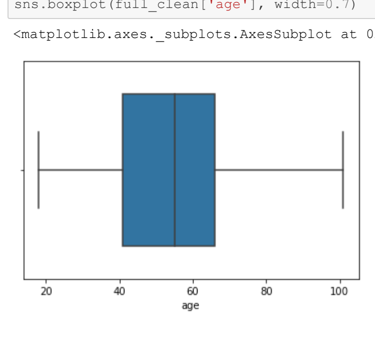
Seems that the age group 45-60 is the most common in customers.

In [36]:
```
full_clean[(full_clean['age'] > 80) & (full_clean['age'] < 102)]['age'].count()
```

Out[36]: 17807

In [37]:
```
sns.boxplot(full_clean['age'], width=0.7)
```

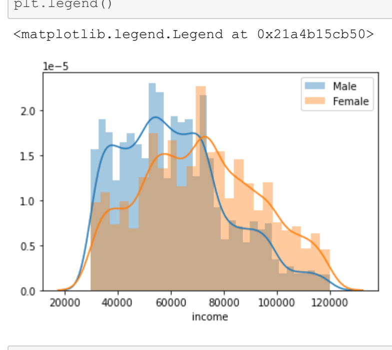
Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x21a4b15b8e0>



It seems that like people with age greater than 80 don't use the app much or they may not drink much beverages. So, I will be considering people with the above age as outliers.

In [38]:
```
# Gender-wise Income Distribution
sns.distplot(profile[profile.gender=='M'].income,label='Male')
sns.distplot(profile[profile.gender=='F'].income,label='Female')
plt.legend()
```

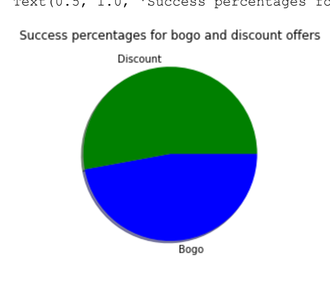
Out[38]: <matplotlib.legend.Legend at 0x21a4b15cb50>



In [39]:
```
success_bogo=((full_clean[(full_clean['bogo']==1.0)&(full_clean['event']=='offer completed')]['event'].
count())/(full_clean[(full_clean['bogo']==1.0)&(full_clean['event']=='offer received')]['event'].count
()))*100
success_discount=((full_clean[(full_clean['discount']==1.0)&(full_clean['event']=='offer completed')][
'event'].count())/(full_clean[(full_clean['discount']==1.0)&(full_clean['event']=='offer received')]['e
vent'].count()))*100
print('Discount success rate: ',success_discount,' Bogo success rate: ',success_bogo)
plt.pie([success_bogo,success_discount],colors=['blue', 'green'], labels=['Bogo', 'Discount'] ,counterc
lock=False, shadow=True)
plt.title('Success percentages for bogo and discount offers')
```

```
Discount success rate:  64.45394539453946  Bogo success rate:  57.497079549308516
```

Out[39]: Text(0.5, 1.0, 'Success percentages for bogo and discount offers')

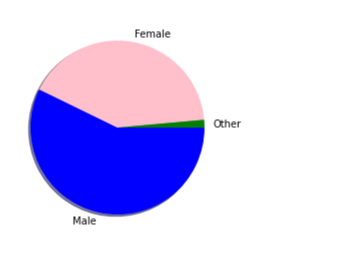


Discount offer is more popular because not only the absolute number of 'offer completed' is slightly higher than BOGO offer, its overall completed/received rate is also about 7% higher. However, BOGO offer has a much greater chance to be viewed or seen by customers.

But this percentage might include the cases when people did not view the offers but completed them unknowingly.

In [40]:
```
plt.pie(profile['gender'].value_counts(), colors=['blue', 'pink', 'green'], labels=['Male', 'Female',
'Other'], counterclock=False, shadow=True)
```

Out[40]:
```
([<matplotlib.patches.Wedge at 0x21a4b27ba90>,
  <matplotlib.patches.Wedge at 0x21a4b2811f0>,
  <matplotlib.patches.Wedge at 0x21a4b2818b0>],
 [Text(-0.24762902922809168, -1.0717648360921126, 'Male'),
  Text(0.19924591390285712, 1.0818045413997002, 'Female'),
  Text(1.098890122095961, 0.049401412529646305, 'Other')])
```



I will be considering only females and males for the simpicity of my further analysis because anyway the other category customers are a very small number.

In [41]:
```
male_bogo_received=full_clean[(full_clean['bogo']==1.0)&(full_clean['event']=='offer received')&(full_c
lean['gender_id']==1)]['event'].count()
male_bogo_completed=full_clean[(full_clean['bogo']==1.0)&(full_clean['event']=='offer completed')&(full
_clean['gender_id']==1)]['event'].count()
female_bogo_received=full_clean[(full_clean['bogo']==1.0)&(full_clean['event']=='offer received')&(full
_clean['gender_id']==0)]['event'].count()
female_bogo_completed=full_clean[(full_clean['bogo']==1.0)&(full_clean['event']=='offer completed')&(fu
ll_clean['gender_id']==0)]['event'].count()
female_success_bogo=((female_bogo_completed)/(female_bogo_received))*100
male_success_bogo=((male_bogo_completed)/(male_bogo_received))*100

print('Female success bogo: ',female_success_bogo,',Male success bogo: ',male_success_bogo)

plt.pie([male_success_bogo,female_success_bogo],colors=['lightblue', 'pink'], labels=['males', 'female
s'] ,counterclock=False, shadow=True)
plt.title('Buy one get one free offer success percentages')
```

```
Female success bogo:  68.34624145785877 ,Male success bogo:  49.39505523408732
```

Out[41]: Text(0.5, 1.0, 'Buy one get one free offer success percentages')

Females are more likely to complete the bogo offer and males have a low offer completion rate

In [42]:
```
male_discount_received=full_clean[(full_clean['discount']==1.0)&(full_clean['event']=='offer received')
&(full_clean['gender_id']==1)]['event'].count()
male_discount_completed=full_clean[(full_clean['discount']==1.0)&(full_clean['event']=='offer complete
d')&(full_clean['gender_id']==1)]['event'].count()
female_discount_received=full_clean[(full_clean['discount']==1.0)&(full_clean['event']=='offer receive
d')&(full_clean['gender_id']==0)]['event'].count()
female_discount_completed=full_clean[(full_clean['discount']==1.0)&(full_clean['event']=='offer complet
ed')&(full_clean['gender_id']==0)]['event'].count()
female_success_discount=((female_discount_completed)/(female_discount_received))*100
male_success_discount=((male_bogo_completed)/(male_bogo_received))*100

print('Female success discount: ',female_success_discount,',Male success discount: ',male_success_disco
unt)

plt.pie([male_success_discount,female_success_discount],colors=['lightblue', 'pink'], labels=['males',
'females'] ,counterclock=False, shadow=True)
plt.title('Discount offer success percentages')
```

```
Female success discount:  72.88677693502696 ,Male success discount:  49.39505523408732
```

Out[42]: Text(0.5, 1.0, 'Discount offer success percentages')

In [43]:
```python
male_bogo_viewed=full_clean[(full_clean['bogo']==1.0)&(full_clean['event']=='offer viewed')&(full_clean['gender_id']==1)]['event'].count()
female_bogo_viewed=full_clean[(full_clean['bogo']==1.0)&(full_clean['event']=='offer viewed')&(full_clean['gender_id']==0)]['event'].count()
male_bogo_received=full_clean[(full_clean['bogo']==1.0)&(full_clean['event']=='offer received')&(full_clean['gender_id']==1)]['event'].count()
female_bogo_received=full_clean[(full_clean['bogo']==1.0)&(full_clean['event']=='offer received')&(full_clean['gender_id']==0)]['event'].count()
female_success_bogo=((female_bogo_viewed)/(female_bogo_received)) *100
male_success_bogo=((male_bogo_viewed)/(male_bogo_received)) *100

print('Female: ',female_success_bogo,', Male: ',male_success_bogo)

plt.pie([female_success_bogo,male_success_bogo],colors=['lightblue', 'pink'], labels=['males', 'females'] ,counterclock=False, shadow=True)
plt.title('Gender likely to view a discount offer')
```

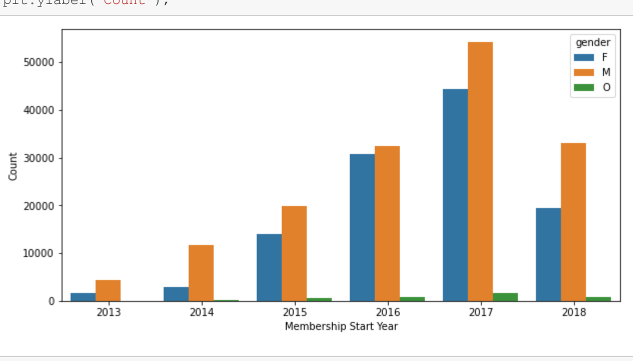
```
Female:  83.30751708428245 , Male:  82.72619673855866
```

Out[43]:
```
Text(0.5, 1.0, 'Gender likely to view a discount offer')
```

The males represent 62.7% of the data and use the Starbucks app more than the females. Specifically, both males & females in the age group 45-60 use app the most. Discount offers are more preferred by the customers.

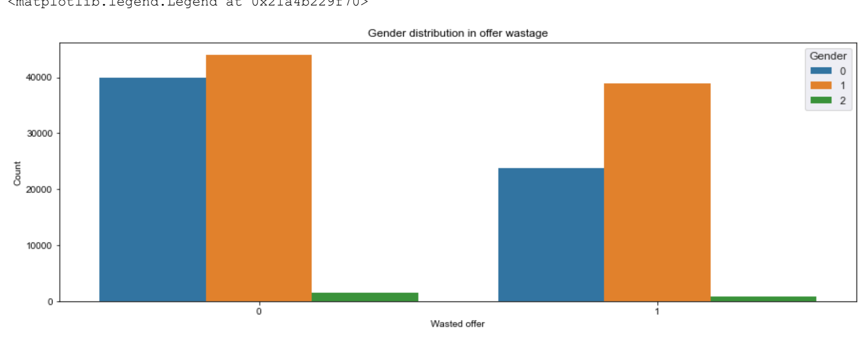
In [44]:
```python
# groupby start_year and gender to plot a graph
full_clean['start_year'] = full_clean.became_member_on.dt.year
membership_date = full_clean.groupby(['start_year', 'gender']).size()
membership_date = membership_date.reset_index()
membership_date.columns = ['start_year', 'gender', 'count']

# plot a bar graph for age distribution as a function of gender in membership program
plt.figure(figsize=(10, 5))
sns.barplot(x='start_year', y='count', hue='gender', data=membership_date)
plt.xlabel('Membership Start Year')
plt.ylabel('Count');
```



In [45]:
```python
plt.figure(figsize=(15, 5))
sns.countplot(x= "wasted", hue= "gender_id", data=df)
sns.set(style="darkgrid")
plt.title('Gender distribution in offer wastage')
plt.ylabel('Count')
plt.xlabel('Wasted offer')
plt.legend(title='Gender')
```

Out[45]:
```
<matplotlib.legend.Legend at 0x21a4b229f70>
```



gender -

0-Female

1-Male

2-Other

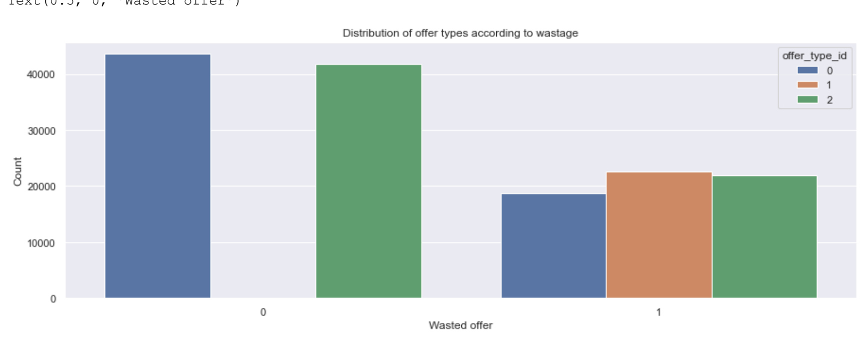
Wasted offer:

0-No

1-Yes

In [46]:
```python
plt.figure(figsize=(15, 5))
sns.countplot(x= "wasted", hue= "offer_type_id", data=df)
sns.set(style="darkgrid")
plt.title('Distribution of offer types according to wastage')
plt.ylabel('Count')
plt.xlabel('Wasted offer')
```

Out[46]:
```
Text(0.5, 0, 'Wasted offer')
```



Offer types:

0-bogo

1-informational

2-discount

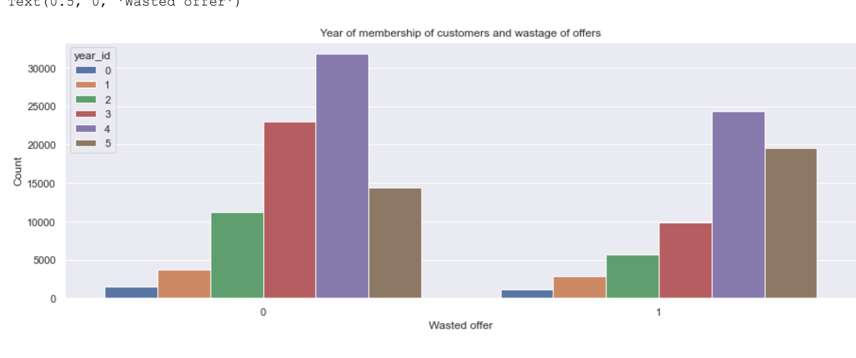
Wasted offer:

0-No

1-Yes

In [47]:
```python
plt.figure(figsize=(15, 5))
sns.countplot(x= "wasted", hue= "year_id", data=df)
sns.set(style="darkgrid")
plt.title('Year of membership of customers and wastage of offers')
plt.ylabel('Count')
plt.xlabel('Wasted offer')
```

Out[47]:
```
Text(0.5, 0, 'Wasted offer')
```



year -

0-'2013'

1-'2014'

2-'2015'

3-'2016'

4-'2017'

5-'2018'

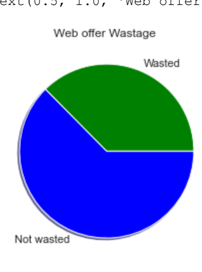
In [48]:
```python
plt.figure(figsize=(15, 5))
sns.countplot(x= "wasted", hue= "duration", data=df)
sns.set(style="darkgrid")
plt.title('Duration(in hours) for the offer to be open and wastage of offers')
plt.ylabel('Count')
plt.xlabel('Wasted offer')
```

Out[48]:
```
Text(0.5, 0, 'Wasted offer')
```

The ideal time for the offer to be open should be 168 hours ie. 7 days for Less number of offers to be wasted

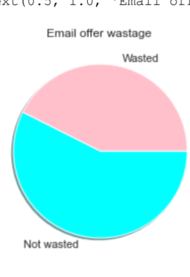
In [49]:
```python
web_not_wasted=df[(df['wasted']==0)&(df['web']==1.0)]['web'].count()
web_wasted=df[(df['wasted']==1)&(df['web']==1.0)]['web'].count()
plt.pie([web_not_wasted,web_wasted],colors=['blue', 'green'], labels=['Not wasted', 'Wasted'] ,counterclock=False, shadow=True)
plt.title('Web offer Wastage ')
```

Out[49]:
```
Text(0.5, 1.0, 'Web offer Wastage ')
```



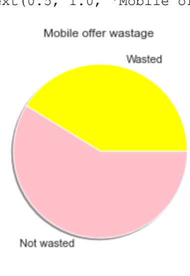
In [50]:
```python
email_not_wasted=df[(df['wasted']==0)&(df['email']==1.0)]['web'].count()
email_wasted=df[(df['wasted']==1)&(df['email']==1.0)]['web'].count()
plt.pie([email_not_wasted,email_wasted],colors=['cyan', 'pink'], labels=['Not wasted', 'Wasted'] ,counterclock=False, shadow=True)
plt.title('Email offer wastage ')
```

Out[50]:
```
Text(0.5, 1.0, 'Email offer wastage ')
```



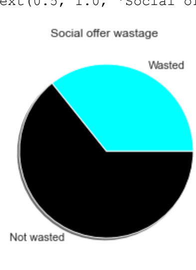
In [51]:
```python
mobile_not_wasted=df[(df['wasted']==0)&(df['mobile']==1.0)]['web'].count()
mobile_wasted=df[(df['wasted']==1)&(df['mobile']==1.0)]['web'].count()
plt.pie([mobile_not_wasted,mobile_wasted],colors=['pink', 'yellow'], labels=['Not wasted', 'Wasted'] ,counterclock=False, shadow=True)
plt.title('Mobile offer wastage ')
```

Out[51]:
```
Text(0.5, 1.0, 'Mobile offer wastage ')
```



In [52]:
```python
social_not_wasted=df[(df['wasted']==0)&(df['social']==1.0)]['web'].count()
social_wasted=df[(df['wasted']==1)&(df['social']==1.0)]['web'].count()
plt.pie([social_not_wasted,social_wasted],colors=['black', 'aqua'], labels=['Not wasted', 'Wasted'] ,counterclock=False, shadow=True)
plt.title('Social offer wastage ')
```

Out[52]:
```
Text(0.5, 1.0, 'Social offer wastage ')
```



Less offers are wasted if sent through mobile or web

Modelling and Evaluation

In [53]:
```python
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.dummy import DummyClassifier
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report


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

from sklearn.model_selection import train_test_split, StratifiedKFold
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassifier
from sklearn.utils.multiclass import unique_labels
from sklearn.metrics import f1_score, precision_score, recall_score, confusion_matrix
import time
```

In [54]:
```python
#want to see how imbalanced is the dataset
df['wasted'].value_counts()
```

Out[54]:
```
0    85429
1    63376
Name: wasted, dtype: int64
```

In [55]:
```python
def model_prep(df):
    #data preperation
    label = df['wasted']
    train = df.iloc[:, 2:].copy()

    #Dividing the data into train and test
    X_train, X_test, y_train, y_test = train_test_split(train, label,test_size=0.30, random_state=1)
    return X_train, X_test, y_train, y_test
```

In [56]:
```python
X_train, X_test, y_train, y_test = model_prep(df)
#dummy model
dummy1 = DummyClassifier(random_state=1).fit(X_train, y_train)
pred_dummy1 = dummy1.predict(X_test)
print("randomly guessing score: {:.2f}".format(dummy1.score(X_test,y_test)))
dummy2 = DummyClassifier(strategy = 'most_frequent').fit(X_train, y_train)
pred_dummy2 = dummy2.predict(X_test)
print("guess all customers will stay score: {:.2f}".format(dummy2.score(X_test,y_test)))
```

```
randomly guessing score: 0.51
guess all customers will stay score: 0.57
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\dummy.py:131: FutureWarning: The default value of strategy will change from stratified to prior in 0.24.
  warnings.warn("The default value of strategy will change from "
```

This shows our class is nearly balanced

In [1]:
```python
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn import svm
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
```

In [2]:
```python
df=pd.read_csv("file1.csv")
df = df.iloc[: , 1:]
df.head()
```

Out[2]:

	person	wasted	age	income	reward	difficulty	duration	web	email	mobile	social	bogo	discount	inf
0	0009655768c64bdeb2e877511632db8f	1	33	72000.0	2.0	10.0	168.0	1.0	1.0	1.0	0.0	0.0	1.0	
1	0009655768c64bdeb2e877511632db8f	1	33	72000.0	2.0	10.0	168.0	1.0	1.0	1.0	0.0	0.0	1.0	
2	0009655768c64bdeb2e877511632db8f	1	33	72000.0	0.0	0.0	96.0	1.0	1.0	1.0	0.0	0.0	0.0	
3	0009655768c64bdeb2e877511632db8f	1	33	72000.0	0.0	0.0	96.0	1.0	1.0	1.0	0.0	0.0	0.0	
4	0009655768c64bdeb2e877511632db8f	1	33	72000.0	0.0	0.0	72.0	0.0	1.0	1.0	1.0	0.0	0.0	

Model preparation

In [4]:
```python
def model_prep(df):
    #data preperation
    label = df['wasted']
    train = df.iloc[:, 2:].copy()

    #Dividing the data into train and test
    X_train, X_test, y_train, y_test = train_test_split(train, label,test_size=0.30, random_state=1)
    return X_train, X_test, y_train, y_test
```

In [5]:
```python
X_train, X_test, y_train, y_test = model_prep(df)

# normalizing some numerical values
scaler=MinMaxScaler()

X_train = pd.DataFrame(MinMaxScaler().fit_transform(X_train), columns=X_train.columns, index=X_train.index)
X_test = pd.DataFrame(MinMaxScaler().fit_transform(X_test), columns=X_test.columns, index=X_test.index)
```

In [ ]:
```python
model_params = {
    'svm': {
        'model': svm.SVC(gamma='auto'),
        'params' : {
            'C': [1,10,20],
            'kernel': ['rbf','linear']
        }
    },
    'random_forest': {
        'model': RandomForestClassifier(),
        'params' : {
            'n_estimators': [1,5,10]
        }
    },
    'logistic_regression' : {
        'model': LogisticRegression(solver='liblinear',multi_class='auto'),
        'params': {
            'C': [1,5,10]
        }
    },
    'naive_bayes_gaussian': {
        'model': GaussianNB(),
        'params': {}
    },
    'naive_bayes_multinomial': {
        'model': MultinomialNB(),
        'params': {}
    },
    'decision_tree': {
        'model': DecisionTreeClassifier(),
        'params': {
            'criterion': ['gini','entropy'],

        }
    }
}
```

In [ ]:
```python
#Time:4 hrs(app)
scores = []

for model_name, mp in model_params.items():
    clf =  GridSearchCV(mp['model'], mp['params'], cv=5, return_train_score=False)
    clf.fit(X_train,y_train)
    scores.append({
        'model': model_name,
        'best_score': clf.best_score_,
        'best_params': clf.best_params_
    })

df = pd.DataFrame(scores,columns=['model','best_score','best_params'])
df.to_csv('file2.csv')
```

In [8]:
```python
import pandas as pd
dfd=pd.read_csv("file2.csv")
dfd=dfd.iloc[:,1:]
dfd
```

Out[8]:

	model	best_score	best_params
0	svm	0.866556	{'C': 20, 'kernel': 'rbf'}
1	random_forest	0.859795	{'n_estimators': 10}
2	logistic_regression	0.826592	{'C': 5}
3	naive_bayes_gaussian	0.806707	{}
4	naive_bayes_multinomial	0.806659	{}
5	decision_tree	0.878007	{'criterion': 'entropy'}

In [9]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

# draw lineplot
sns.lineplot(x="model", y="best_score", data=dfd).set_title('Model vs Best scores')

sns.set(rc={'figure.figsize':(12,5)})
plt.show()
```

Conclusion

The problem that I chose to solve was to build a model that predicts whether a customer will respond to an offer.

The following observations were made after the exploratory data analysis:

The age group 45-60 is the most common in customers. Most Customers have income ranging between 50000-70000. Discount offer is more popular because not only the absolute number of 'offer completed' is slightly higher than BOGO offer, its overall completed/received rate is also about 7% higher.

Females are more likely to complete the bogo or discount offer and males have a low offer completion rate It seems to be that people with age greater than 80 don't use the app much or they may not drink many beverages. There is one entry for age 118. I will be considering it an outlier.

Buy one get one free offer is less likely to get wasted and most of the informational offers are most likely to get wasted.
Customers who joined in 2017 are less likely to waste an offer.

The ideal time for the offer to be open should be 168 hours ie. 7 days Less number of offers is wasted if offers are sent through social media or web.

The most common offer type among all age groups is the BOGO , followed by the Discount Offers. Whereas, the least common offer to be sent is the informational offers. I believe that BOGO offers are more attractive compared to other offers provided by Starbucks.

After splitting data to train and test datasets, I chose the best estimator "DecisionTreeClassifier" using GridSearch which is the best performing classifier algorithm among the above 6 classifiers tested. After performing hyper parameter tuning, I built the model. An accuracy of 87.8 was achieved by the model.

In [ ]: