Starbucks_Capstone_notebook

December 29, 2021

1 Starbucks Capstone Challenge

1.0.1 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.

1.0.2 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.

1.0.3 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.

1.0.4 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).

2 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

2.1 1 - Business Understanding

1) The main purpose of studying this dataset is to understand the customer behavior on the Starbucks rewards mobile app. This data, which is simulated and mimics customer behavior, respects only to one product. The purpose is to understand the customer behaviour and answer questions like:

- demographic distribution of clients;
- its preferences by age and gender; who are more likely to respond to promotions, etc. ####

2) It will lead us to more conscious decision, including proportion strategies; ####
3) That knowledge, that, in this case, respects only to one product, will also allow us to verify if the same kind of behaviour is observed in other products and related promotions; ####
4) The focus in the present work is to analyse data in order to answer some of the enumerated questions (and others) and create a model that will predict, with accuracy, the customer behaviour.

2.2 2 - Data Understanding

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import math
import json
import datetime
import seaborn as sns
from collections import defaultdict
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import RandomForestRegressor
from sklearn.multioutput import MultiOutputClassifier
from sklearn.datasets import make_multilabel_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import Pipeline
%matplotlib inline
```

[2]:
```
# read in the json files
portfolio = pd.read_json('Starbucks_data/portfolio.json', orient='records',␣
 ↪lines=True)
profile = pd.read_json('Starbucks_data/profile.json', orient='records',␣
 ↪lines=True)
transcript = pd.read_json('Starbucks_data/transcript.json', orient='records',␣
 ↪lines=True)
```

2.2.1 2.1 - First Look at the data

2.1.1) All datasets

[3]:
```
portfolio
```

[3]:
```
   reward                      channels  difficulty  duration     offer_type  \
0      10       [email, mobile, social]          10         7           bogo
1      10  [web, email, mobile, social]          10         5           bogo
2       0          [web, email, mobile]           0         4  informational
3       5          [web, email, mobile]           5         7           bogo
```

```
4       5                  [web, email]          20          10         discount
5       3  [web, email, mobile, social]           7           7         discount
6       2  [web, email, mobile, social]          10          10         discount
7       0       [email, mobile, social]           0           3    informational
8       5  [web, email, mobile, social]           5           5             bogo
9       2          [web, email, mobile]          10           7         discount

                                 id
0  ae264e3637204a6fb9bb56bc8210ddfd
1  4d5c57ea9a6940dd891ad53e9dbe8da0
2  3f207df678b143eea3cee63160fa8bed
3  9b98b8c7a33c4b65b9aebfe6a799e6d9
4  0b1e1539f2cc45b7b9fa7c272da2e1d7
5  2298d6c36e964ae4a3e7e9706d1fb8c2
6  fafdcd668e3743c1bb461111dcafc2a4
7  5a8bc65990b245e5a138643cd4eb9837
8  f19421c1d4aa40978ebb69ca19b0e20d
9  2906b810c7d4411798c6938adc9daaa5
```

[141]:
```
profile.head()
```

[141]:
```
  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
```

[96]:
```
transcript.tail() #finding number of hours of test duration (714h)
```

[96]:
```
                                  person        event  \
306529  b3a1272bc9904337b331bf348c3e8c17  transaction
306530  68213b08d99a4ae1b0dcb72aebd9aa35  transaction
306531  a00058cf10334a308c68e7631c529907  transaction
306532  76ddbd6576844afe811f1a3c0fbb5bec  transaction
306533  c02b10e8752c4d8e9b73f918558531f7  transaction

                                   value  time
306529  {'amount': 1.5899999999999999}   714
306530                {'amount': 9.53}   714
306531                {'amount': 3.61}   714
306532  {'amount': 3.5300000000000002}   714
306533                {'amount': 4.05}   714
```

[5]:
```
#shape of datasets
print(portfolio.shape)
print(profile.shape)
print(transcript.shape)
```

```
(10, 6)
```

```
(17000, 5)
(306534, 4)
```

[12]:
```
# find columns with nulls
col_null_portfolio = portfolio.isnull().sum()
col_null_profile = profile.isnull().sum()
col_null_transcript = transcript.isnull().sum()
print(col_null_portfolio)
print(col_null_profile)
print(col_null_transcript)
```

```
reward        0
channels      0
difficulty    0
duration      0
offer_type    0
id            0
dtype: int64
gender              2175
age                    0
id                     0
became_member_on       0
income              2175
dtype: int64
person    0
event     0
value     0
time      0
dtype: int64
```

[53]:
```
#unique values in transcript

event_unique = transcript['event'].unique()
count_by_event = transcript['event'].value_counts()
print(event_unique)
print(count_by_event)
```

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

2.2.2 2.2 - First Look at the data: profile dataset - demographic characterization

[111]:
```
#ages interval investigation
profile.age.value_counts() #there is some error with 'age == 118' : assuming␣
 ↪it's a null value
```

[111]:
```
118    2175
58      408
53      372
51      363
54      359
       ...
100      12
96        8
98        5
101       5
99        5
Name: age, Length: 85, dtype: int64
```

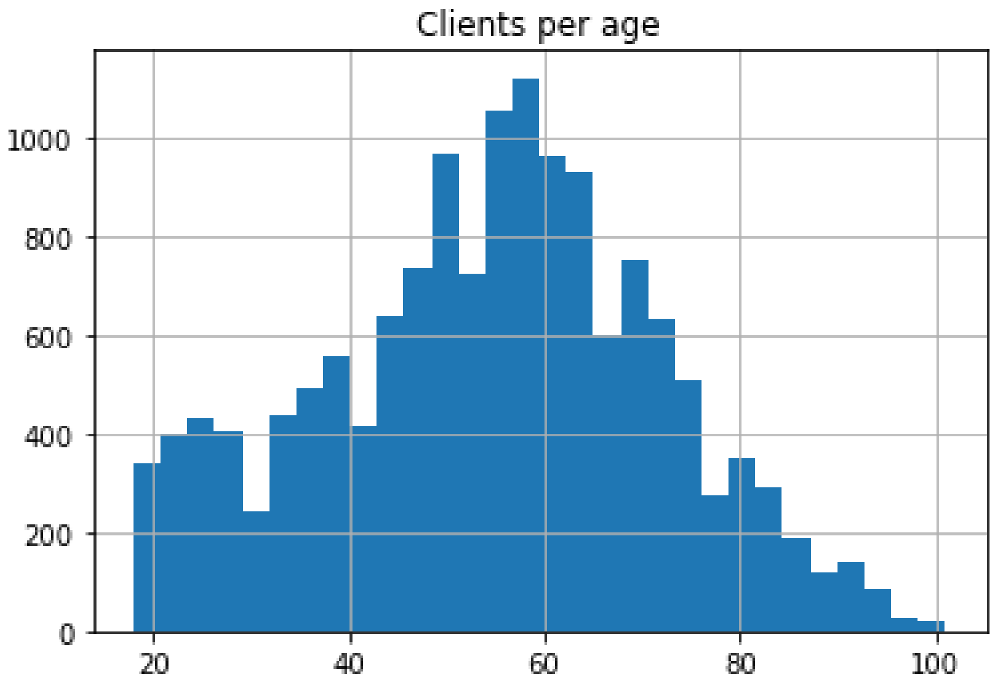
[7]:
```
#remove age==118
profile_drop_null = profile[profile.age != 118]
```

[63]:
```
#percentage of nulls, particularly in age
age_nulls = profile[profile['age']==118].count()/profile['age'].shape[0]
age_nulls
```

[63]:
```
gender              0.000000
age                 0.127941
id                  0.127941
became_member_on    0.127941
income              0.000000
age_groups          0.000000
dtype: float64
```

[8]:
```
# ages of clients
profile_drop_null.age.hist(bins = 30)
plt.title('Clients per age')
```

[8]:
```
Text(0.5, 1.0, 'Clients per age')
```

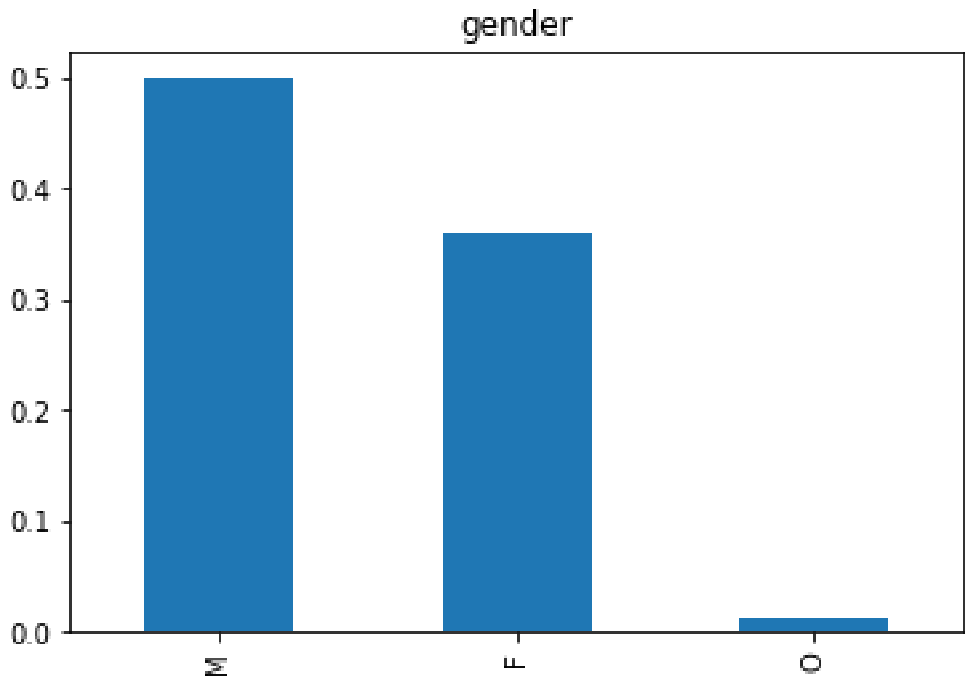


[106]:
```
profile.gender.value_counts()
```

[106]:
```
M    8484
F    6129
O     212
Name: gender, dtype: int64
```

[32]:
```
genders= profile.gender.value_counts()
(genders/profile.shape[0]).plot(kind="bar")
plt.title('gender')
```

[32]:
```
Text(0.5, 1.0, 'gender')
```

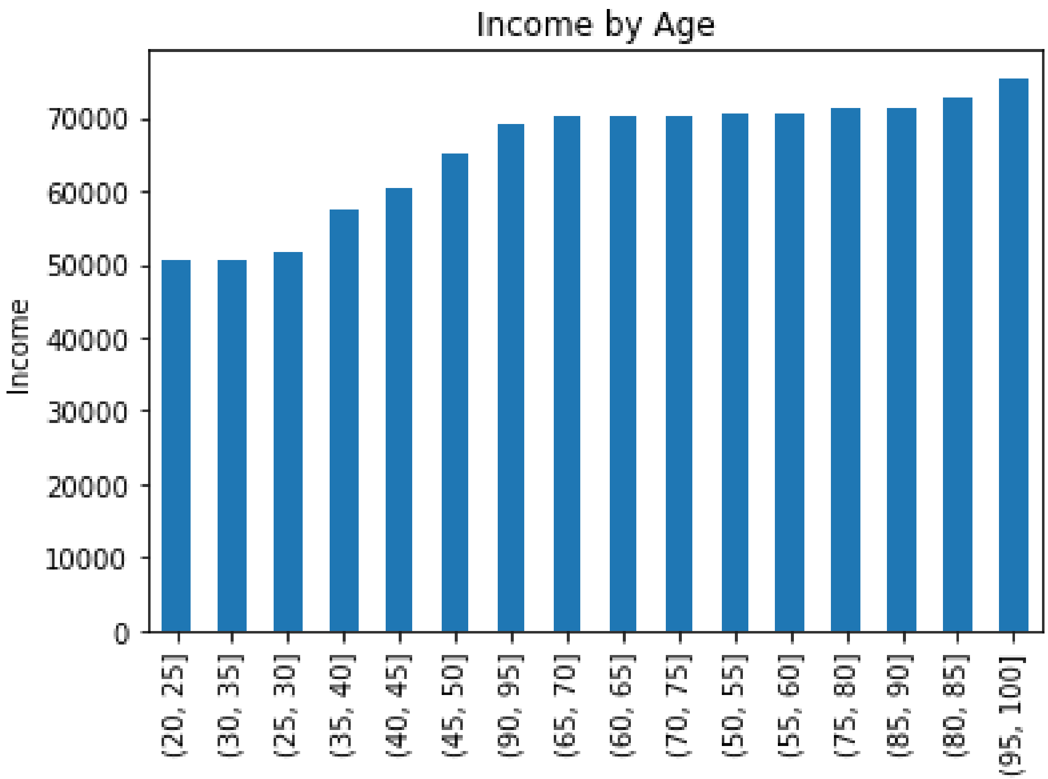


[22]:
```
profile["age_groups"] = pd.cut(profile['age'],␣
↪bins=[20,25,30,35,40,45,50,55,60,65,70,75,80,85,90,95,100])
```

[23]:
```
income_by_age = profile.groupby(['age_groups']).mean()['income'].sort_values().
↪dropna()
```

[28]:
```
income_by_age.plot(kind="bar")
plt.title('Income by Age')

plt.xlabel('Age')
plt.ylabel("Income")
plt.show()
```



[18]:
```
profile_description = profile[profile.age != 118] #ignore the null values
```

[19]:
```
# look at statistcs description
profile_description[['age', 'income']].describe()
```

[19]:

	age	income
count	14825.000000	14825.000000
mean	54.393524	65404.991568
std	17.383705	21598.299410
min	18.000000	30000.000000
25%	42.000000	49000.000000
50%	55.000000	64000.000000
75%	66.000000	80000.000000
max	101.000000	120000.000000

2.3 3 - Data Preparation

2.3.1 3.1 - Clean and transform the data

3.1.1 - Clean and transform portfolio dataframe

[3]:
```
def transform_portfolio(dataframe):
    """
```

```
    clean and trandfor the portfolio dataframe

    INPUT: dataframe to be cleaned
    OUTPUT: portfolio dataframe transformed
    """
    #convert number of days into hours: the same metric in column time in␣
↪transcript dataframe
    portfolio['duration'] = portfolio['duration']*24

    #rename column id to offer_id (considering column value of transcript␣
↪dataframe)
    portfolio.rename(columns={'id':'offer_id'},inplace=True)
    return portfolio
```

[4]:
```
portfolio = transform_portfolio(portfolio)
```

[6]:
```
portfolio.head(10)
```

[6]:
```
   reward                      channels  difficulty  duration     offer_type  \
0      10       [email, mobile, social]          10       168           bogo
1      10  [web, email, mobile, social]          10       120           bogo
2       0          [web, email, mobile]           0        96  informational
3       5          [web, email, mobile]           5       168           bogo
4       5                  [web, email]          20       240       discount
5       3  [web, email, mobile, social]           7       168       discount
6       2  [web, email, mobile, social]          10       240       discount
7       0       [email, mobile, social]           0        72  informational
8       5  [web, email, mobile, social]           5       120           bogo
9       2          [web, email, mobile]          10       168       discount

                           offer_id
0  ae264e3637204a6fb9bb56bc8210ddfd
1  4d5c57ea9a6940dd891ad53e9dbe8da0
2  3f207df678b143eea3cee63160fa8bed
3  9b98b8c7a33c4b65b9aebfe6a799e6d9
4  0b1e1539f2cc45b7b9fa7c272da2e1d7
5  2298d6c36e964ae4a3e7e9706d1fb8c2
6  fafdcd668e3743c1bb461111dcafc2a4
7  5a8bc65990b245e5a138643cd4eb9837
8  f19421c1d4aa40978ebb69ca19b0e20d
9  2906b810c7d4411798c6938adc9daaa5
```

[5]:
```
portfolio.columns
```

[5]:
```
Index(['reward', 'channels', 'difficulty', 'duration', 'offer_type',
       'offer_id'],
      dtype='object')
```

3.1.2 - Clean and transform profile dataframe

[5]:
```
def transform_profile(df):
    """
    clean and transform the profile dataframe

    INPUT: dataframe to be cleaned
    OUTPUT: profile dataframe transformed
    """
    # drop all null values
    profile.dropna(inplace = True)

    #age classification, also promote data anonimity
    profile.loc[(profile.age < 25) , 'age_range'] = '< 25'
    profile.loc[(profile.age >= 25) & (profile.age < 35) , 'age_range'] =␣
↪'25-34'
    profile.loc[(profile.age >= 35) & (profile.age < 45) , 'age_range'] =␣
↪'35-44'
    profile.loc[(profile.age >= 45) & (profile.age < 55) , 'age_range'] =␣
↪'45-54'
    profile.loc[(profile.age >= 55) & (profile.age < 65) , 'age_range'] =␣
↪'55-64'
    profile.loc[(profile.age >= 65) & (profile.age < 75) , 'age_range'] =␣
↪'65-74'
    profile.loc[(profile.age >= 75) & (profile.age <= 85) , 'age_range'] =␣
↪'75-85'
    profile.loc[(profile.age > 85) , 'age_range'] = '> 85'

    #rename id column to costumer_id
    #(avoid disambiguation with offer_id and match transcript dataframe column)
    profile.rename(columns={'id':'customer_id'},inplace=True)

    #convert became_member_on column to datetime
    profile['became_member_on']=pd.to_datetime(profile['became_member_on'],␣
↪format='%Y%m%d')

    return profile
```

[6]:
```
profile = transform_profile(profile)
```

[9]:
```
profile.head()
```

[9]:
```
   gender  age                       customer_id became_member_on    income  \
1       F   55  0610b486422d4921ae7d2bf64640c50b       2017-07-15  112000.0
3       F   75  78afa995795e4d85b5d9ceeca43f5fef       2017-05-09  100000.0
5       M   68  e2127556f4f64592b11af22de27a7932       2018-04-26   70000.0
8       M   65  389bc3fa690240e798340f5a15918d5c       2018-02-09   53000.0
12      M   58  2eeac8d8feae4a8cad5a6af0499a211d       2017-11-11   51000.0

   age_range
```

```
1      55-64
3      75-85
5      65-74
8      65-74
12     55-64
```

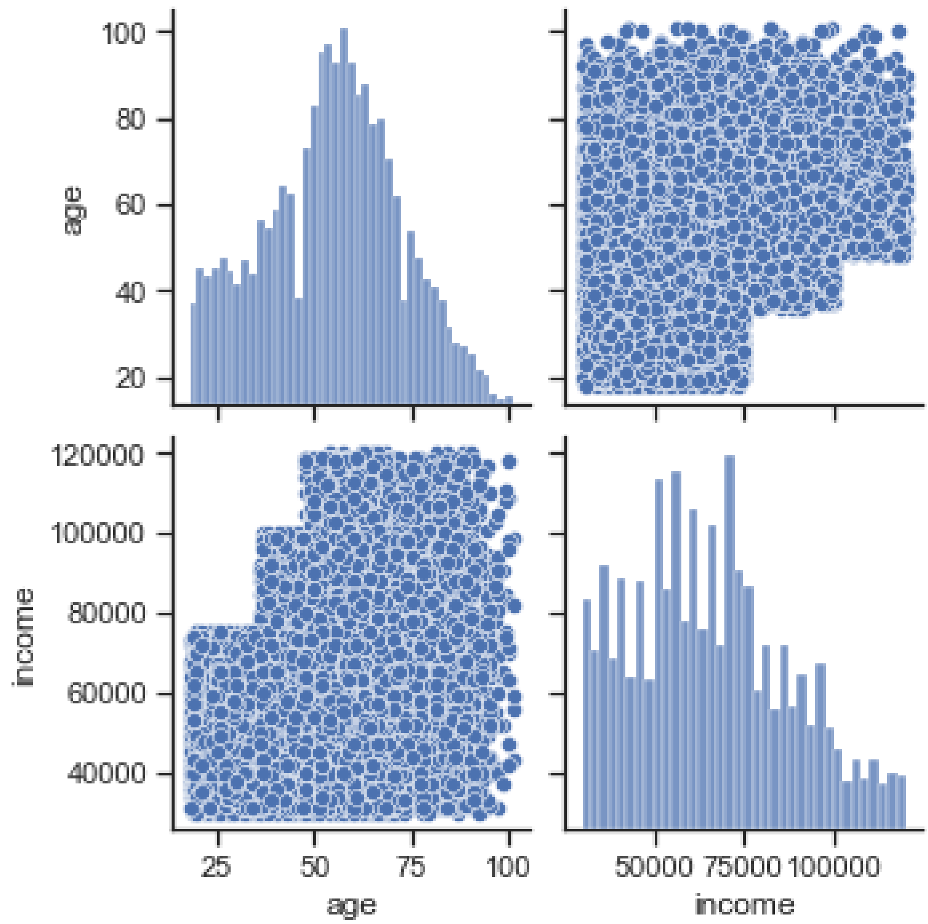
[11]:
```
#age mean, median, standard deviation
age_mean = (profile['age'].mean())
age_median = profile['age'].median()
age_st_dev = profile['age'].std()
age_max = profile['age'].max()
age_min = profile['age'].min()
print('The mean of ages is {}.'.format(round(age_mean,1)))
print('The median of ages is {}.'.format(age_median))
print('The standard deviation is {}.'.format(round(age_st_dev,5)))
print('The higher age is {}.'.format(age_max))
print('The lower age is {}'.format(age_min))
```

```
The mean of ages is 54.4.
The median of ages is 55.0.
The standard deviation is 17.38371.
The higher age is 101.
The lower age is 18
```

[95]:
```
income_mean = profile['income'].mean()
income_median= profile['income'].median()
income_max = profile['income'].max()
income_min = profile['income'].min()
income_std = profile['income'].std()
print('The mean of income is {}.'.format(round(income_mean,3)))
print('The median of income is {}.'.format(round(income_median,3)))
print('The standard deviation is {}.'.format(round(income_std,3)))
print('The higher income is {}.'.format(income_max))
print('The lower income is {}'.format(income_min))
```

```
The mean of income is 65404.992.
The median of income is 64000.0.
The standard deviation is 21598.299.
The higher income is 120000.0.
The lower income is 30000.0
```

[72]:
```
#observe income vs age
sns.set(style="ticks", color_codes=True)
income_age= profile[['age', 'income']]
g = sns.pairplot(income_age)
plt.show()
```

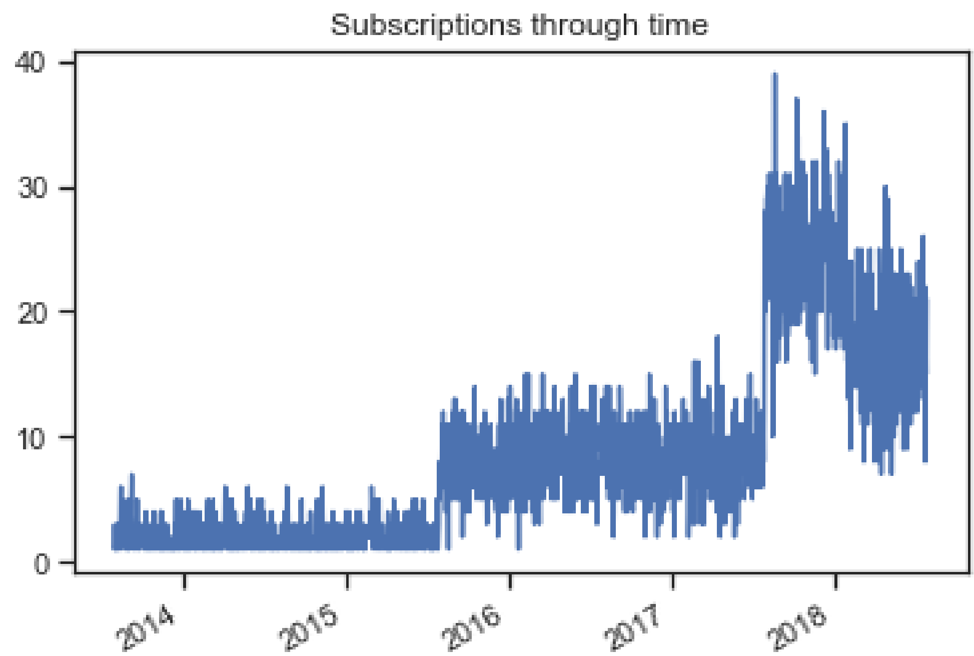


[96]:
```
older_member_date = profile['became_member_on'].max()
recent_member_date = profile['became_member_on'].min()
print('The older date member is {}.'.format(older_member_date))
print('The recent date member is {}.'.format(recent_member_date))
```

```
The older date member is 2018-07-26 00:00:00.
The recent date member is 2013-07-29 00:00:00.
```

[106]:
```
y=profile['became_member_on'].value_counts()
y.plot.line()
plt.title('Subscriptions through time')
```

[106]:
```
Text(0.5, 1.0, 'Subscriptions through time')
```



3.1.3 - Clean and transform transcript dataframe

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

[28]:
```
                             person           event  \
0  78afa995795e4d85b5d9ceeca43f5fef  offer received
1  a03223e636434f42ac4c3df47e8bac43  offer received
2  e2127556f4f64592b11af22de27a7932  offer received
3  8ec6ce2a7e7949b1bf142def7d0e0586  offer received
4  68617ca6246f4fbc85e91a2a49552598  offer received

                                              value  time
0  {'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}     0
1  {'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}     0
2  {'offer id': '2906b810c7d4411798c6938adc9daaa5'}     0
3  {'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}     0
4  {'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}     0
```

[7]:
```
def transform_transcript(df):
    """
    clean and transform the transcript dataframe

    INPUT: dataframe to be cleaned
    OUTPUT: profile dataframe transformed
    """
    #rename person column to customer_id in order to match profile dataframe
```

```
    transcript.rename(columns={'person':'customer_id'},inplace=True)

    #isolate and process classifications in value column
    values = []
    for val, unique in transcript.iterrows():
        for val in unique['value']:
            if val in values:
                continue
            else:
                values.append(val)
    for val, unique in transcript.iterrows():
        for i in unique['value']:
            if val == 'offer_id' or i == 'offer id':
                transcript.at[val, 'offer_id'] = unique['value'][i]
            if i == 'amount':
                transcript.at[val, 'amount'] = unique['value'][i]
            if i == 'reward':
                transcript.at[val, 'reward'] = unique['value'][i]
    transcript.drop('value', axis=1, inplace=True)

    return transcript
```

[8]:
```
transcript = transform_transcript(transcript)
```

[9]:
```
#replace all null values with 0
transcript = transcript.fillna(0)
```

[10]:
```
transcript.head()
```

[10]:
```
                        customer_id           event  time  \
0  78afa995795e4d85b5d9ceeca43f5fef  offer received     0
1  a03223e636434f42ac4c3df47e8bac43  offer received     0
2  e2127556f4f64592b11af22de27a7932  offer received     0
3  8ec6ce2a7e7949b1bf142def7d0e0586  offer received     0
4  68617ca6246f4fbc85e91a2a49552598  offer received     0

                           offer_id  amount  reward
0  9b98b8c7a33c4b65b9aebfe6a799e6d9     0.0     0.0
1  0b1e1539f2cc45b7b9fa7c272da2e1d7     0.0     0.0
2  2906b810c7d4411798c6938adc9daaa5     0.0     0.0
3  fafdcd668e3743c1bb461111dcafc2a4     0.0     0.0
4  4d5c57ea9a6940dd891ad53e9dbe8da0     0.0     0.0
```

[13]:
```
transcript['event'].value_counts()
```

[13]:
```
transaction        138953
offer received      76277
offer viewed        57725
offer completed     33579
Name: event, dtype: int64
```

[10]:
```
#create dummy variables from event
transcript['transaction'] = transcript['event'].apply(lambda event: 1 if␣
↪'transaction' in event else 0)
transcript['offer_received'] = transcript['event'].apply(lambda event: 1 if␣
↪'offer received' in event else 0)
transcript['offer_viewed'] = transcript['event'].apply(lambda event: 1 if␣
↪'offer viewed' in event else 0)
transcript['offer_completed'] = transcript['event'].apply(lambda event: 1 if␣
↪'offer completed' in event else 0)
```

3.1.4 - Merge dataframes

[11]:
```
#merge transcript dataframe with profile dataframe by customer_id column
df = pd.merge(transcript, portfolio, on='offer_id',how='outer')
```

[14]:
```
#check columns of df
df.shape
```

[14]:
```
(306534, 15)
```

[12]:
```
#merge new df dataframe with portfolio dataframe
df =pd.merge(df,profile,on='customer_id', how='outer')
```

[12]:
```
df.shape
```

[12]:
```
(306534, 20)
```

[13]:
```
#check df columns
df.columns
```

[13]:
```
Index(['customer_id', 'event', 'time', 'offer_id', 'amount', 'reward_x',
       'transaction', 'offer_received', 'offer_viewed', 'offer_completed',
       'reward_y', 'channels', 'difficulty', 'duration', 'offer_type',
       'gender', 'age', 'became_member_on', 'income', 'age_range'],
      dtype='object')
```

[13]:
```
df['event'].value_counts()
```

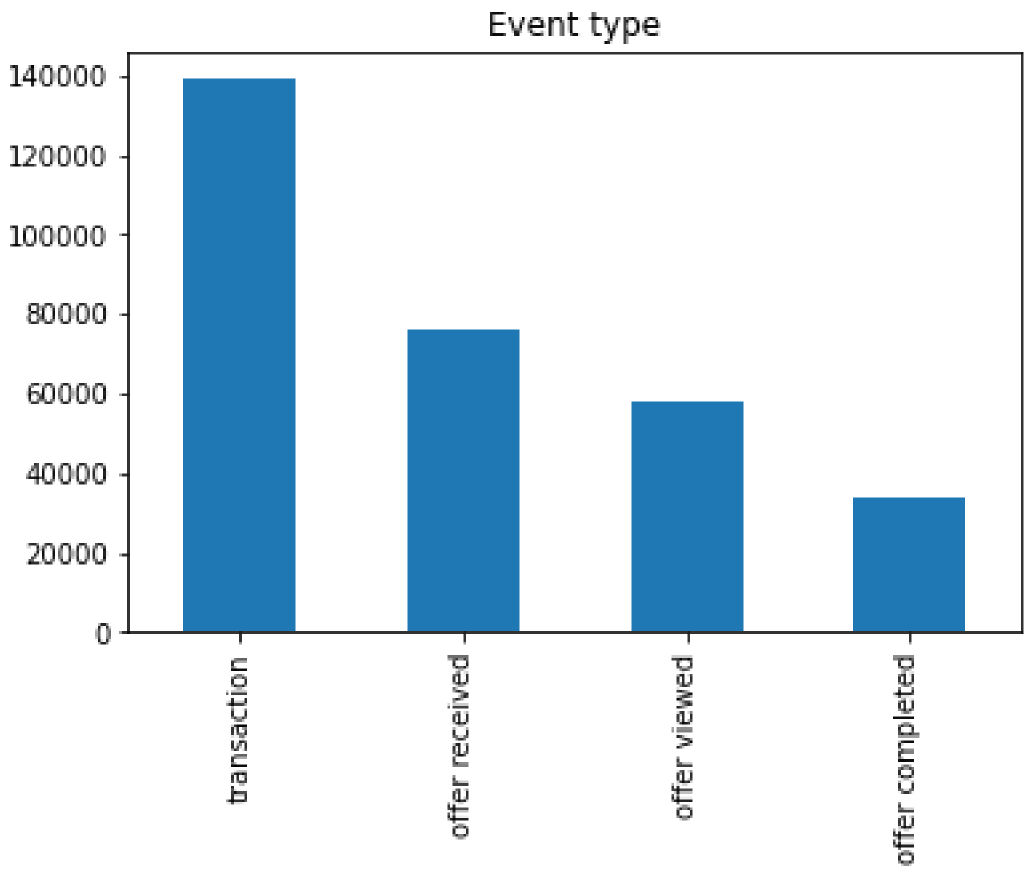
[13]:
```
transaction        138953
offer received      76277
offer viewed        57725
offer completed     33579
Name: event, dtype: int64
```

2.3.2 3.1.5 - Some more questioning on data

i) Count Event type

[12]:
```
df['event'].value_counts().plot(kind="bar")
plt.title('Event type')
```

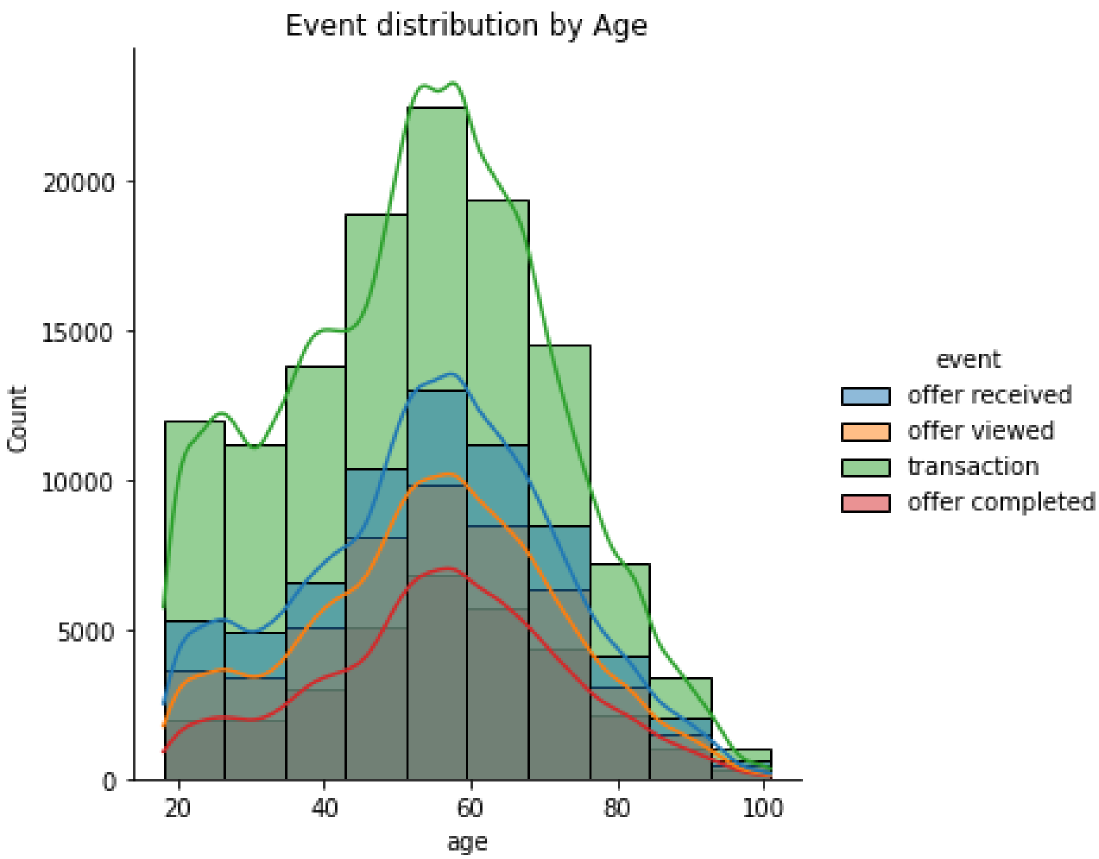
[12]:
```
Text(0.5, 1.0, 'Event type')
```



ii) Distribution of event type by age

[14]:
```
sns.displot(x ='age',kde=True, bins=10,
hue = df['event'] ,data=df)
plt.title('Event distribution by Age')
```

[14]:
```
Text(0.5, 1.0, 'Event distribution by Age')
```

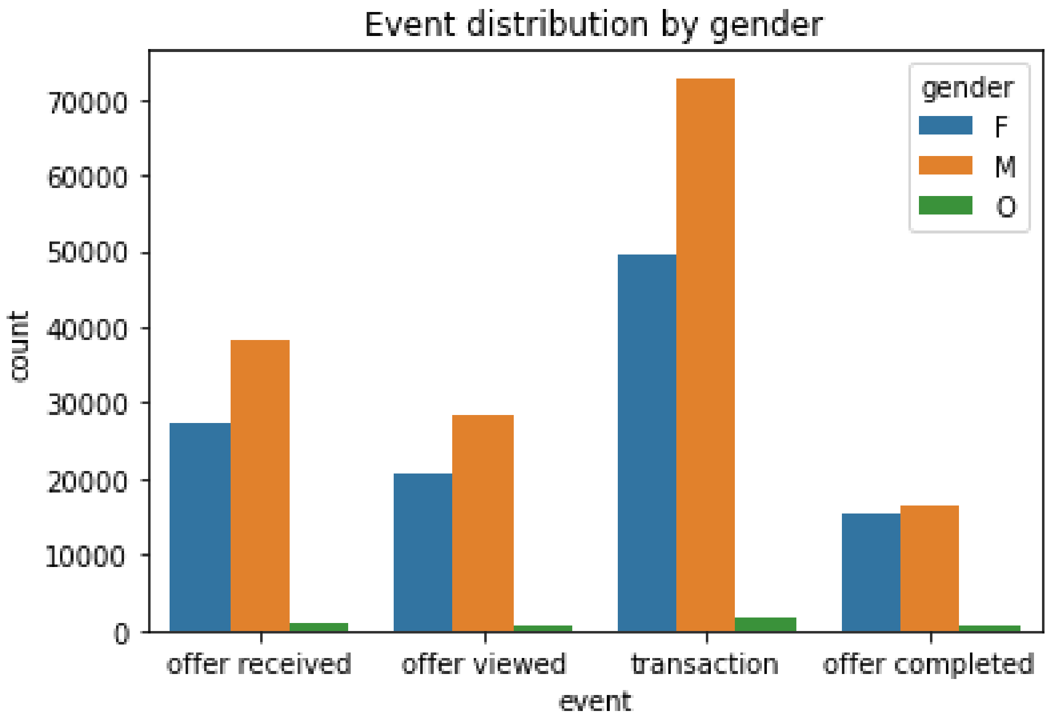


We can observe that people above 55 and under 65 are more likely to view, receive and complete offers, as well as transactions.

iii) Distribution of event type by genderű

[19]:
```
sns.countplot(x= "event", hue= "gender", data=df)
plt.title('Event distribution by gender')
```

[19]: `Text(0.5, 1.0, 'Event distribution by gender')`



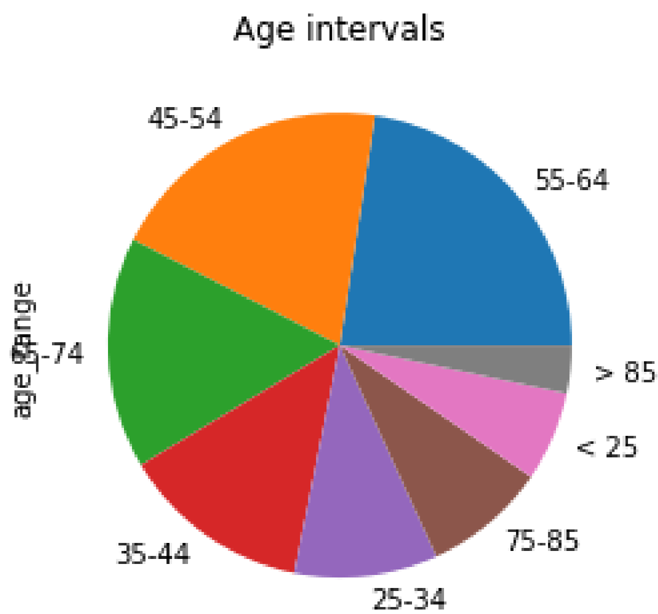
iv) Is the age group [55-64] the most represented group?

[17]:
```
round(df['age_range'].value_counts()/df.shape[0],2)
```

[17]:
```
55-64    0.20
45-54    0.18
65-74    0.14
35-44    0.12
25-34    0.09
75-85    0.08
< 25     0.06
> 85     0.03
Name: age_range, dtype: float64
```

[16]:
```
ages =(df['age_range'].value_counts()/df.shape[0])
ages.plot(kind='pie', normalize=True)
plt.title('Age intervals')
```

[16]:
```
Text(0.5, 1.0, 'Age intervals')
```

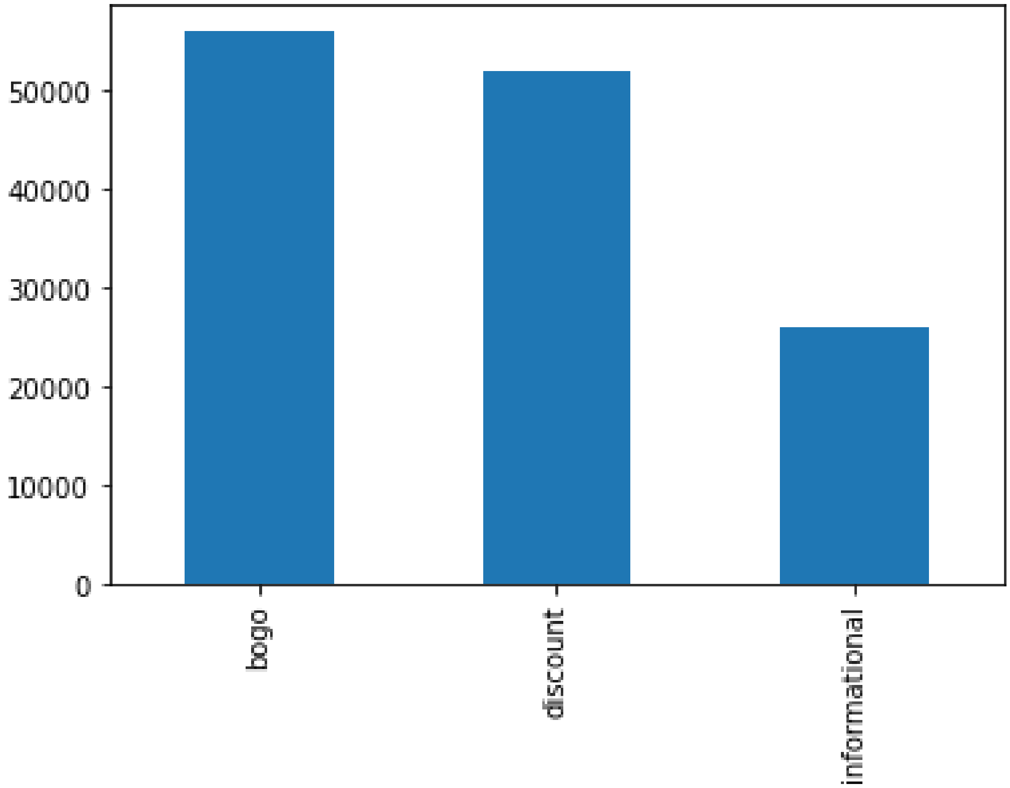


It is the most represented age group, although it will not explain all the causes of this most active behaviour.

v) Count of offer_type

[117]:
```
kind_of_offer = df['offer_type'].value_counts()
kind_of_offer.plot(kind="bar")
```

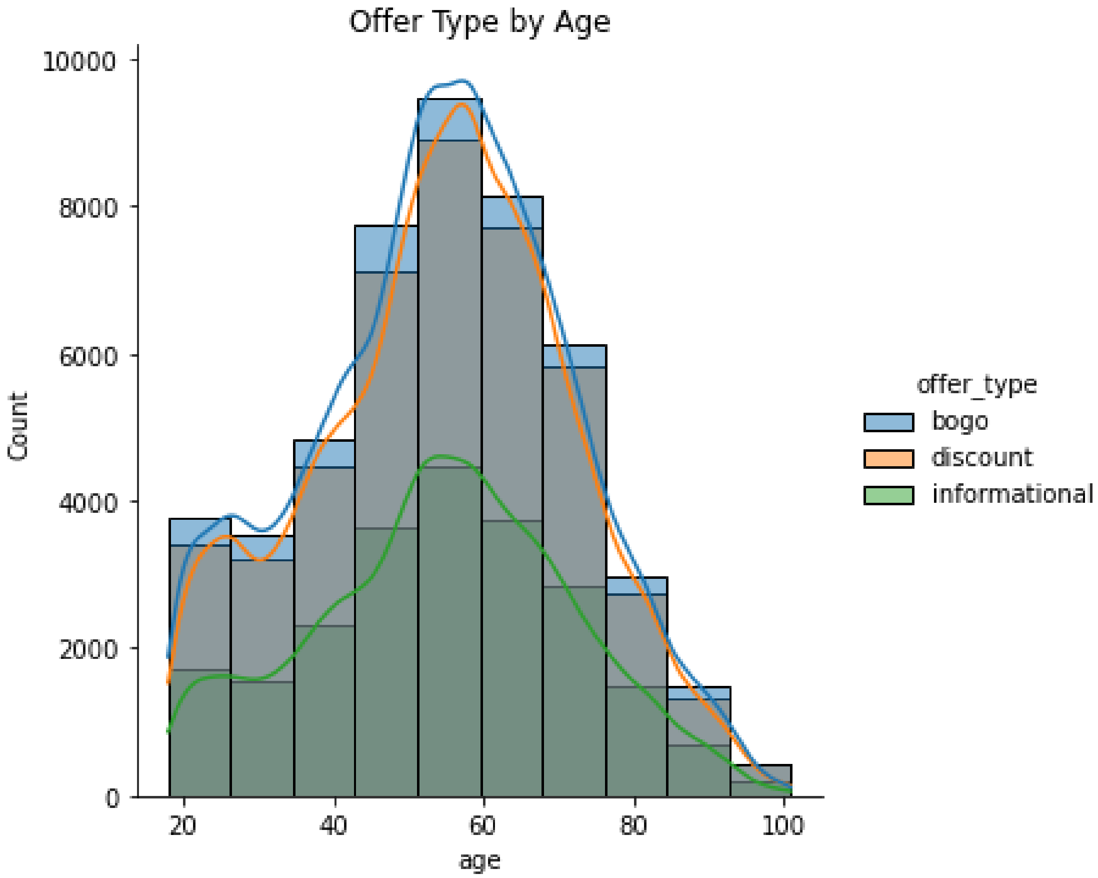
[117]: <AxesSubplot:>



vi) Offer Type by age

[118]:
```
sns.displot(x ='age',kde=True, bins=10,
hue = df['offer_type'] ,data=df)
plt.title('Offer Type by Age')
```

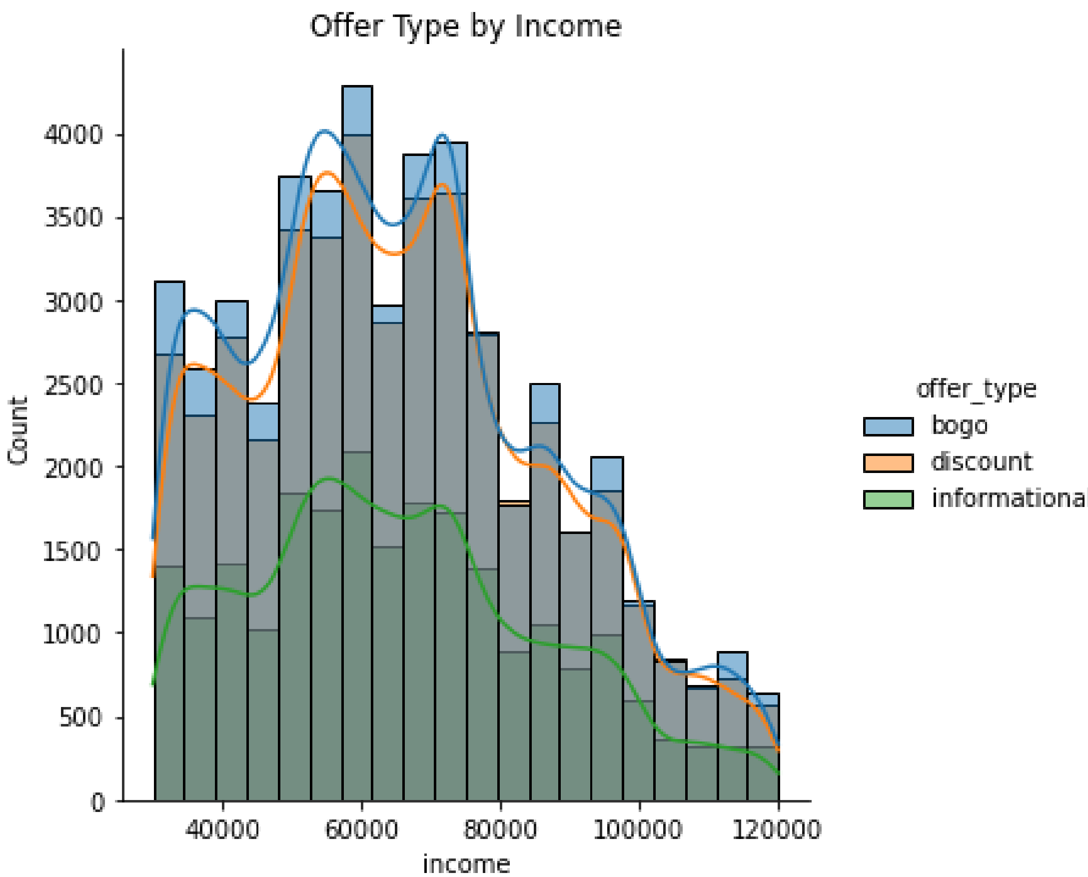
[118]: Text(0.5, 1.0, 'Offer Type by Age')



vii) Offer type by Income

[122]:
```
sns.displot(x ='income',kde=True,bins=20,
hue = df['offer_type'] ,data=df)
plt.title('Offer Type by Income')
```

[122]:
```
Text(0.5, 1.0, 'Offer Type by Income')
```



We can't say that the higher the income the higher the usage of offer types, but we can see an accentuated decrease in incomes above 80.000.

viii) Offer type by gender

[16]:
```
sns.countplot(x= "offer_type", hue= "gender", data=df)
plt.title("Offer Type by gender")
```

[16]:
```
Text(0.5, 1.0, 'Offer Type by gender')
```

ix) Analyse the possible channels usage to reach clients

[59]:
```
possible_medium=['web','email','mobile','social']
```

[72]:
```
medium=medium.value_counts().reset_index()
medium.rename(columns={'index': 'channel', 'channels': 'count'}, inplace=True)
```

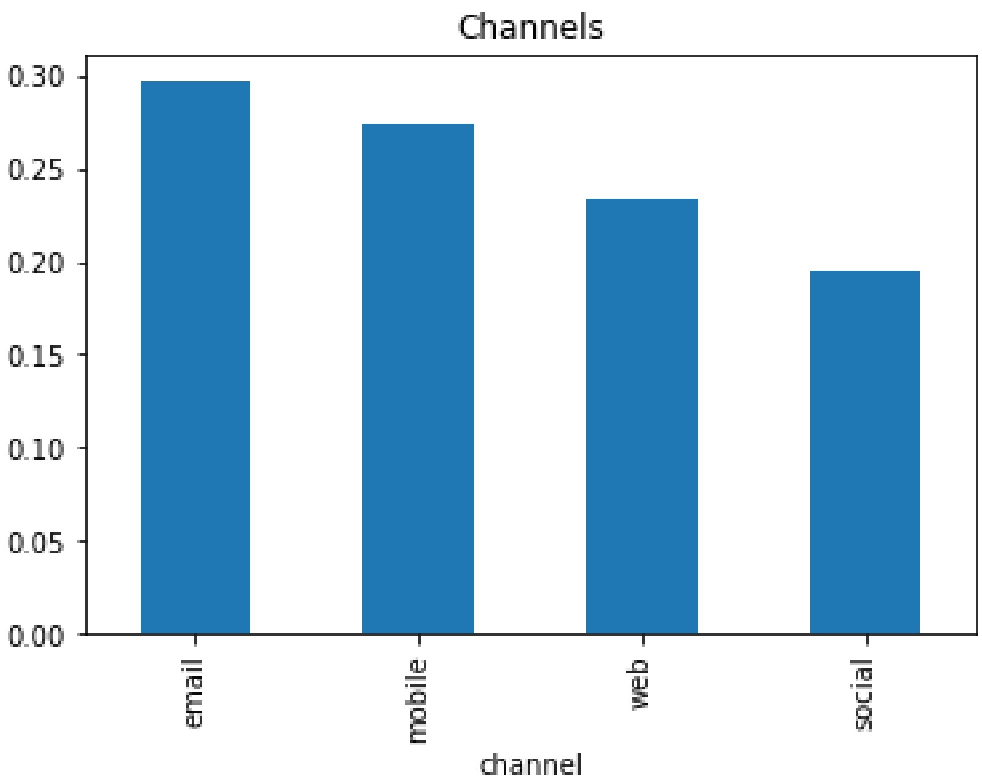
[79]:
```
def channel_count(df, col1, col2, str_list):
    '''
    INPUT:
    df - the pandas dataframe
    col_1 - column name we want to look through
    col_2 - column we want to count values from
    str_list - a list where we look in each row

    OUTPUT:
    new_df - the dataframe that show up the counting
    '''
    new_df = defaultdict(int)
    for ch in str_list:
        for idx in range(df.shape[0]):
            if ch in df[col1][idx]:
                new_df[ch] += int(df[col2][idx])
    new_df = pd.DataFrame(pd.Series(new_df)).reset_index()
```

```python
    new_df.columns = [col1, col2]
    new_df.sort_values('count', ascending=False, inplace=True)
    return new_df
```

[82]:
```python
channel_df = channel_count(medium, 'channel', 'count', possible_medium)
channel_df.set_index('channel', inplace=True)
```

[83]:
```python
## results with the percent
channel_df['perc'] = channel_df['count']/np.sum(channel_df['count'])
## plot bar chart
(channel_df['perc']).plot(kind="bar")
title= 'Channels'
plt.title(title)
plt.show()
```



[21]:
```python
df.columns
```

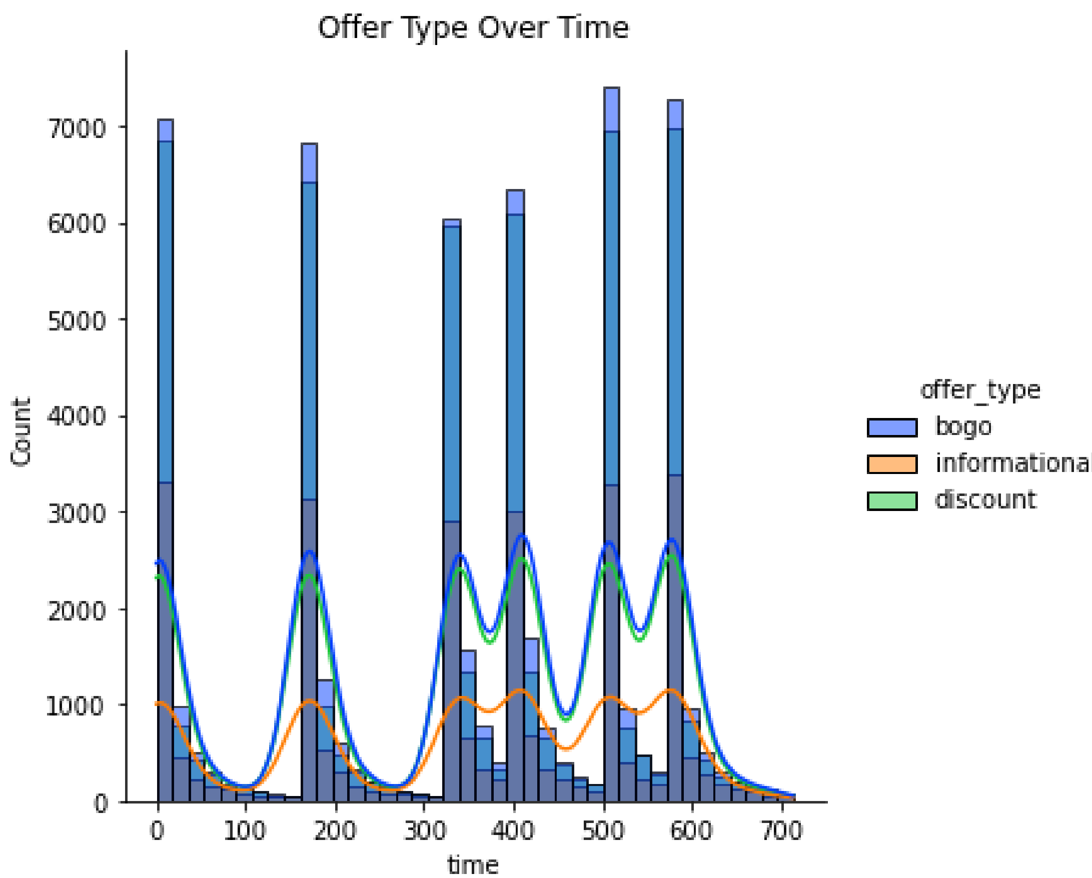
[21]:
```
Index(['customer_id', 'event', 'time', 'offer_id', 'amount', 'reward_x',
       'transaction', 'offer received', 'offer viewed', 'offer completed',
       'reward_y', 'channels', 'difficulty', 'duration', 'offer_type',
       'gender', 'age', 'became_member_on', 'income', 'age_range'],
      dtype='object')
```

x) Check behaviour of Offer Type across Time

[23]:
```
sns.displot(data=df,x ='time',kde=True,bins=40,
hue = df['offer_type'],palette=sns.color_palette('bright',3))
plt.title('Offer Type Over Time')
```

[23]:
```
Text(0.5, 1.0, 'Offer Type Over Time')
```

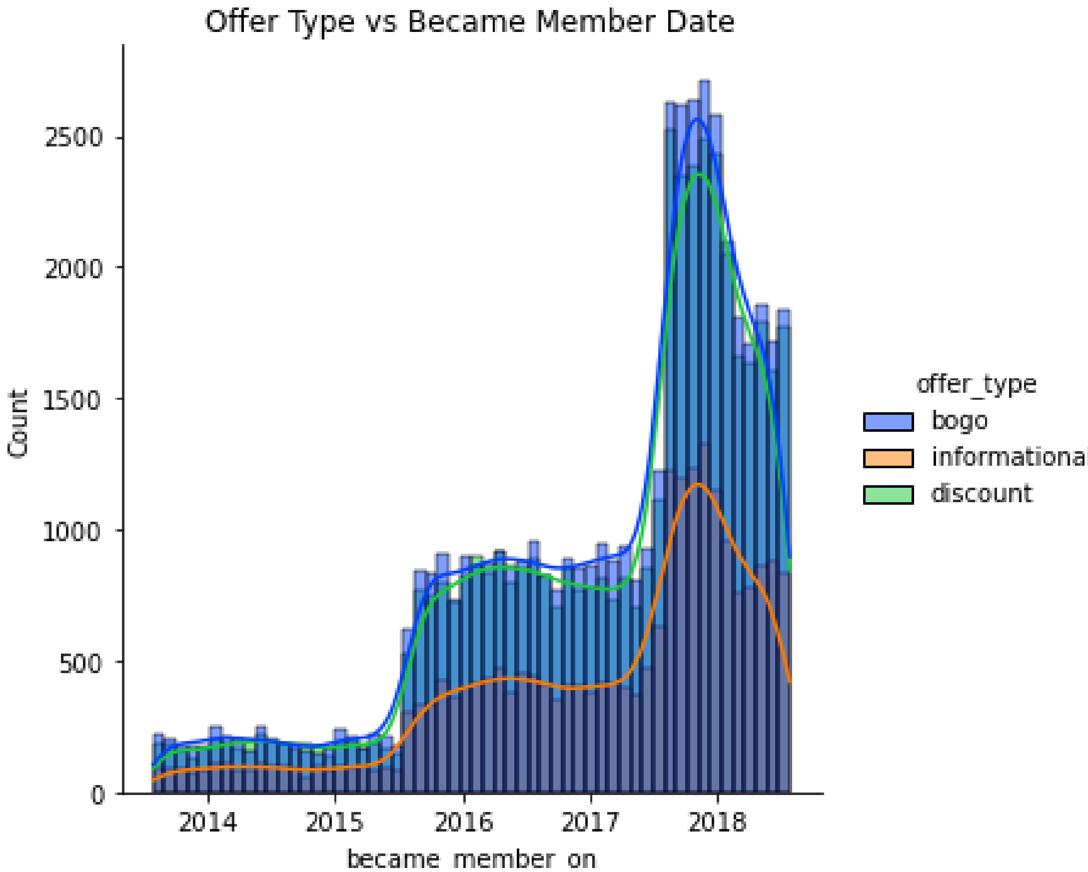
```
<Figure size 1008x288 with 0 Axes>
```



xi) Check behaviour of offer time through date of new members admitions

[31]:
```
sns.displot(x ='became_member_on',kde=True,bins=56,
hue = df['offer_type'], palette=sns.color_palette('bright',3),data=df)
plt.title('Offer Type vs Became Member Date')
```

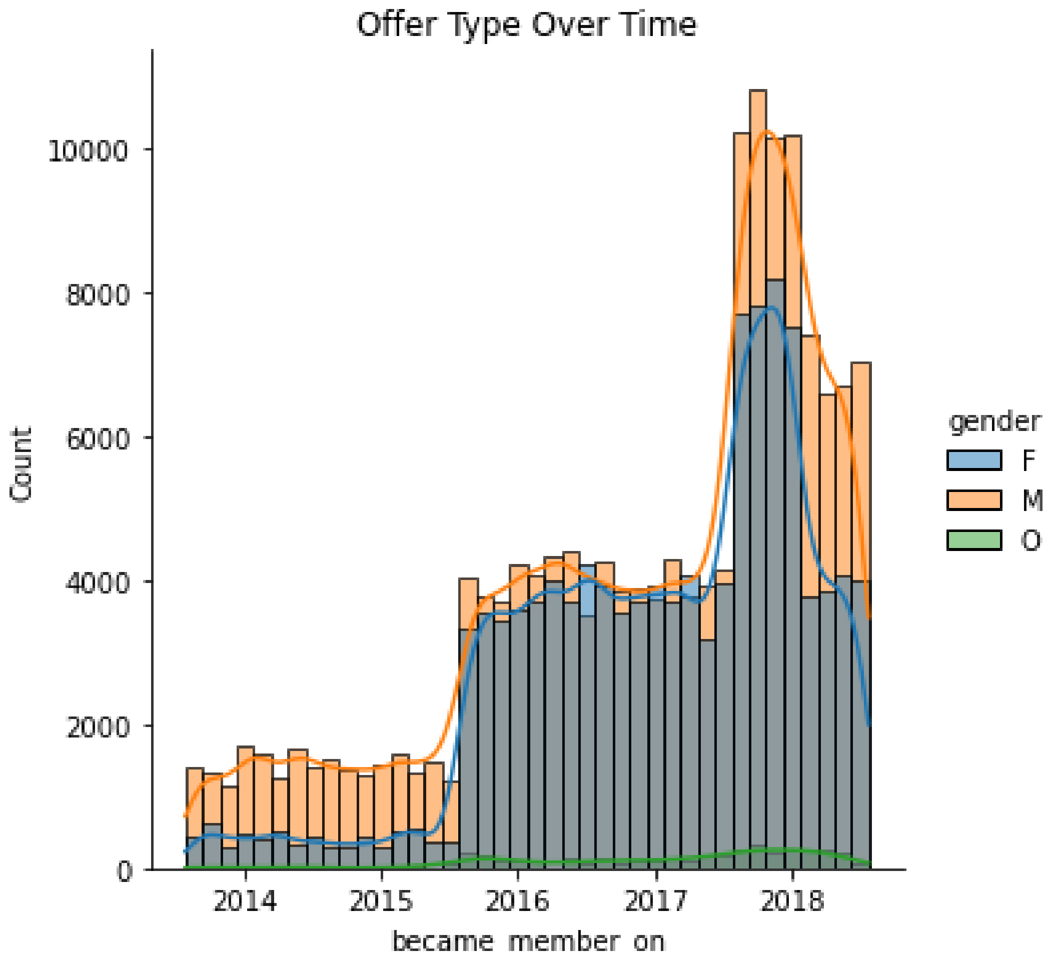
[31]:
```
Text(0.5, 1.0, 'Offer Type vs Became Member Date')
```



xii) Check behaviour of member admission by gender

[18]:
```
sns.displot(data=df,x ='became_member_on',kde=True,bins=40,
hue = df['gender'])
plt.title('Became Member Date vs gender')
```

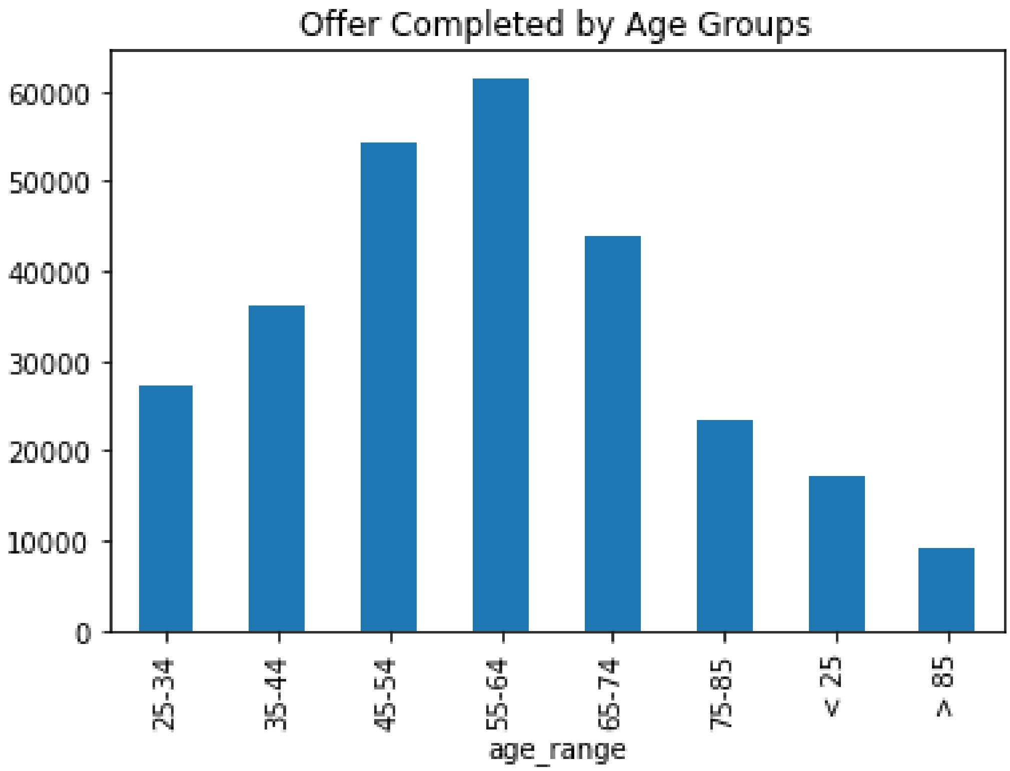
[18]:
```
Text(0.5, 1.0, 'Offer Type Over Time')
```



xiii) From demographics, check who are more likely to complete an offer

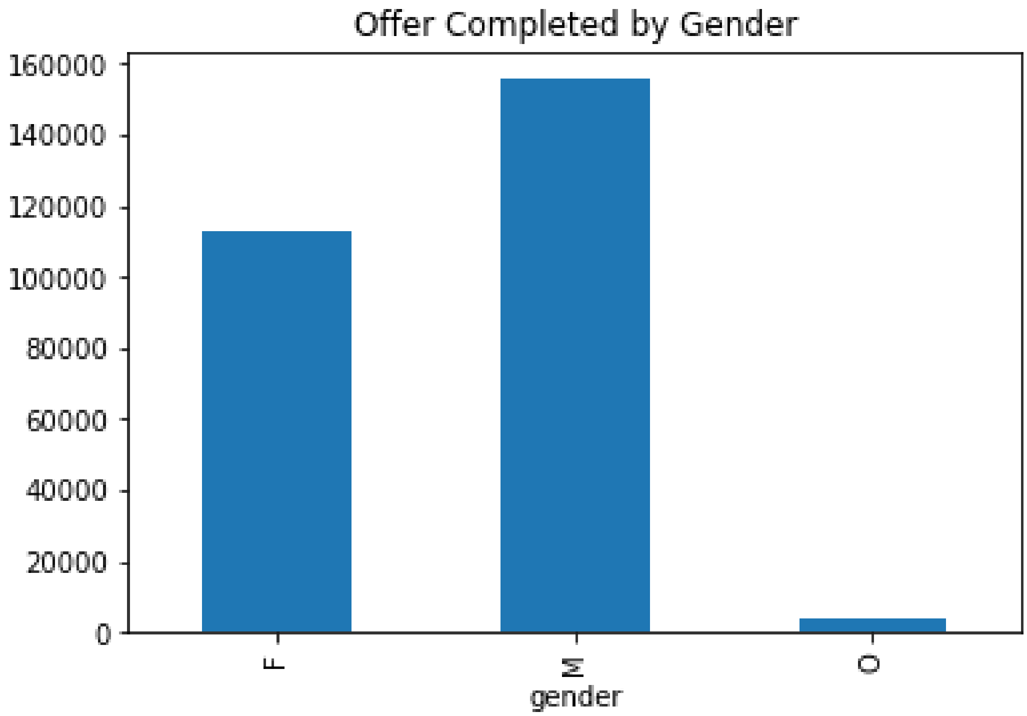
[45]:
```
age_complete=df.groupby('age_range')['offer_completed'].count()
age_complete.plot(kind='bar')
plt.title('Offer Completed by Age Groups')
```

[45]:
```
Text(0.5, 1.0, 'Offer Completed by Age Groups')
```



[34]:
```
g=df.groupby('gender')['offer_completed'].count()
g.plot(kind='bar')
plt.title('Offer Completed by Gender')
```

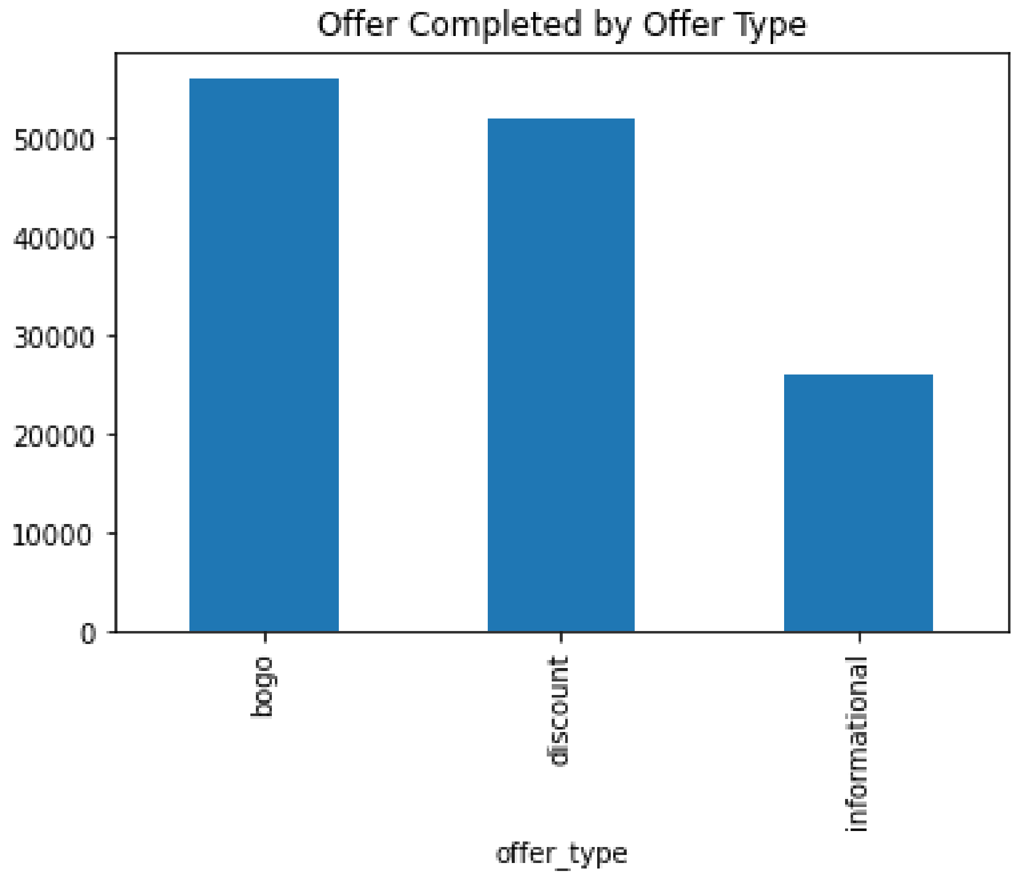
[34]:
```
Text(0.5, 1.0, 'Offer Completed by Gender')
```



xiv) Offer Completed by Offer Type

[46]:
```
gender_compl=df.groupby('offer_type')['offer_completed'].count()
gender_compl.plot(kind='bar')
plt.title('Offer Completed by Offer Type')
```

[46]: Text(0.5, 1.0, 'Offer Completed by Offer Type')



We can see that those who have received 'bogo' or 'discount' were more likely to complete an offer.

xv) Find correlations in dataframe

[14]:
```
df=df.fillna(0)
df.drop(['reward_y'],axis=1, inplace=True)
```

[15]:
```
df.corr()
```

[15]:
```
                     time    amount  reward_x  transaction  offer_received  \
time             1.000000  0.023626  0.047534     0.069098       -0.097121
amount           0.023626  1.000000 -0.080783     0.298108       -0.156237
reward_x         0.047534 -0.080783  1.000000    -0.270986       -0.171283
transaction      0.069098  0.298108 -0.270986     1.000000       -0.524097
offer_received  -0.097121 -0.156237 -0.171283    -0.524097        1.000000
offer_viewed    -0.029075 -0.130751 -0.143342    -0.438602       -0.277229
offer_completed  0.060702 -0.095210  0.848470    -0.319382       -0.201873
difficulty      -0.080217 -0.175891 -0.192830    -0.590025        0.504420
duration        -0.098907 -0.217989 -0.238981    -0.731241        0.606979
```

```
age              0.004654  0.083167  0.085733    -0.034062       -0.012370
income           0.000975  0.134200  0.118928    -0.066641       -0.005174

                 offer_viewed  offer_completed  difficulty  duration  \
time                -0.029075         0.060702   -0.080217 -0.098907
amount              -0.130751        -0.095210   -0.175891 -0.217989
reward_x            -0.143342         0.848470   -0.192830 -0.238981
transaction         -0.438602        -0.319382   -0.590025 -0.731241
offer_received      -0.277229        -0.201873    0.504420  0.606979
offer_viewed         1.000000        -0.168942    0.375030  0.484880
offer_completed     -0.168942         1.000000   -0.227267 -0.281662
difficulty           0.375030        -0.227267    1.000000  0.889699
duration             0.484880        -0.281662    0.889699  1.000000
age                 -0.014464         0.089522   -0.016226 -0.019624
income              -0.006408         0.121405   -0.005277 -0.007479

                      age    income
time             0.004654  0.000975
amount           0.083167  0.134200
reward_x         0.085733  0.118928
transaction     -0.034062 -0.066641
offer_received  -0.012370 -0.005174
offer_viewed    -0.014464 -0.006408
offer_completed  0.089522  0.121405
difficulty      -0.016226 -0.005277
duration        -0.019624 -0.007479
age              1.000000  0.653439
income           0.653439  1.000000
```

we can observe significant positive correlations (>0.5) between:

- age and income (0.6534)

- duration an difficulty (0.8897)

- reward and difficulty (0.7385)

- duration and reward (0.6573)

- duration and offer_received (0.6070)

- difficulty and duration (0.8897)

- offer_completed and reward(0.848470)

There is also a low correlation (<0.5) between offer_viewed and duration (0.4848)

we can also observe significant negative correlations between:

- duration and transaction (-0.7312)

2.3.3 4 - Modeling the data

I) Final cleanning: one more step - clean the dataset before modeling

a) drop some columns

[16]:
```
# more clean on df
df.drop(['event'],axis=1, inplace=True)
df.rename(columns={'reward_x':'reward'},inplace=True)
```

[17]:
```
#also remove channels, which we have already analyse
df.drop(['channels'],axis=1, inplace=True)
```

b) rearrange some variables (from string to integer type)

. rearrange ages with integers, replacing the strings

18 - 25 : 1;

25 - 34: 2;

35 - 44: 3;

45 - 54: 4;

55 - 64: 5;

65 - 74: 6;

75 - 84: 7;

> 85 :8;

[18]:
```
df.loc[(df.age < 25) , 'age_range'] = 1
df.loc[(df.age >= 25) & (df.age < 35) , 'age_range'] = 2
df.loc[(df.age >= 35) & (df.age < 45) , 'age_range'] = 3
df.loc[(df.age >= 45) & (df.age < 55) , 'age_range'] = 4
df.loc[(df.age >= 55) & (df.age < 65) , 'age_range'] = 5
df.loc[(df.age >= 65) & (df.age < 75) , 'age_range'] = 6
df.loc[(df.age >= 75) & (df.age <= 85) , 'age_range'] = 7
df.loc[(df.age > 85) , 'age_range'] = 8
```

[19]:
```
#remove age, which we have already analyse
df.drop(['age'],axis=1, inplace=True)
```

. rearrange offer_id and costumer_id

[20]:
```
# replace with integer the string in costumer_id
costm_id = df['customer_id'].astype('category').cat.categories.tolist()
costm_id = {'customer_id' : {c: i for c,i in␣
↪zip(costm_id,list(range(1,len(costm_id)+1)))}}

# replace categorical labels with numeric
df.replace(costm_id, inplace=True)
```

[21]:
```
# replace with integer the string in costumer_id
off_id = df['offer_id'].astype('category').cat.categories.tolist()
off_id = {'offer_id' : {c: i for c,i in␣
↪zip(off_id,list(range(1,len(off_id)+1)))}}

# replace categorical labels with numeric
df.replace(off_id, inplace=True)
```

. replace strings in offer_type:

1: bogo

2: discount

3: informational

[23]:
```
df.loc[(df.offer_type == 'bogo') , 'offer_type'] = 1
df.loc[(df.offer_type == 'discount') , 'offer_type'] = 2
df.loc[(df.offer_type == 'informational') , 'offer_type'] = 3
```

replace gender letters by numbers:

F -> 1

M -> 2

O -> 3

[37]:
```
df.loc[(df.gender == 'F') , 'gender'] = 1
df.loc[(df.gender == 'M') , 'gender'] = 2
df.loc[(df.gender == 'O') , 'gender'] = 3
```

4.1) X and Y definition;

Transaction will be excluded

[38]:
```
#Define X and Y
#we'll not consider transaction
#we'll not consider date of membership (analysed appart)

X = df[['customer_id', 'time', 'offer_id', 'amount', 'reward', 'difficulty',
        'duration', 'offer_type', 'gender', 'income','age_range']]
y = df[['offer_received', 'offer_viewed', 'offer_completed']]
```

[39]:
```
X.head()
```

[39]:
```
   customer_id  time  offer_id  amount  reward  difficulty  duration  \
0         7997     0         8     0.0     0.0         5.0     168.0
1         7997     6         8     0.0     0.0         5.0     168.0
2         7997   504        10     0.0     0.0         5.0     120.0
3         7997   582        10     0.0     0.0         5.0     120.0
4         7997   408         9     0.0     0.0        10.0     168.0

  offer_type gender    income age_range
0          1      1  100000.0         7
1          1      1  100000.0         7
2          1      1  100000.0         7
3          1      1  100000.0         7
4          1      1  100000.0         7
```

II) Start modeling data

Split into train and test set

[40]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.3,␣
 ↪random_state = 42)
```

Check shape of train and test set

[41]:
```
print("The train set has {} rows".format(X_train.shape[0]))
print("The test set has {} rows".format(X_test.shape[0]))
```

```
The train set has 214573 rows
The test set has 91961 rows
```

RandomForestClassifier

[60]:
```
#create pipeline
pipeline = Pipeline([
    ('clf',MultiOutputClassifier(RandomForestClassifier()))
])
```

[61]:
```
#fit pipeline
pipeline.fit(X_train, y_train)
```

[61]:
```
Pipeline(steps=[('clf',
                 MultiOutputClassifier(estimator=RandomForestClassifier()))])
```

[62]:
```
# predict y
y_pred = pipeline.predict(X_test)
```

Test the model

[63]:
```
# find accuracy
accuracy = (y_pred == y_test).mean()
print(accuracy)
```

```
offer_received     0.905601
offer_viewed       0.900121
offer_completed    1.000000
dtype: float64
```

[41]:
```
target_names=y.columns
print(classification_report(y_test, y_pred, target_names = target_names))
```

```
                 precision    recall  f1-score   support

 offer_received       0.79      0.83      0.81     22886
   offer_viewed       0.76      0.70      0.73     17295
offer_completed       1.00      1.00      1.00     10141

      micro avg       0.82      0.82      0.82     50322
      macro avg       0.85      0.84      0.85     50322
   weighted avg       0.82      0.82      0.82     50322
    samples avg       0.45      0.45      0.45     50322


/Users/anateresaneto/opt/miniconda3/envs/my_env/lib/python3.9/site-
packages/sklearn/metrics/_classification.py:1248: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in samples with no
predicted labels. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/anateresaneto/opt/miniconda3/envs/my_env/lib/python3.9/site-
packages/sklearn/metrics/_classification.py:1248: UndefinedMetricWarning: Recall
and F-score are ill-defined and being set to 0.0 in samples with no true labels.
Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

KNeighborsClassifier

[56]:
```
#create pipeline
pipeline = Pipeline([
    ('clf',MultiOutputClassifier(KNeighborsClassifier()))
```

```
])
```

[57]:
```
#fit pipeline
pipeline.fit(X_train, y_train)
```

[57]:
```
Pipeline(steps=[('clf',
                 MultiOutputClassifier(estimator=KNeighborsClassifier()))])
```

[58]:
```
# predict y
y_pred = pipeline.predict(X_test)
```

Test the model

[59]:
```
#find accuracy to first evaluation of the model
accuracy = (y_pred == y_test).mean()
print(accuracy)
```

```
offer_received     0.736606
offer_viewed       0.755984
offer_completed    0.879112
dtype: float64
```

[46]:
```
target_names=y.columns
print(classification_report(y_test, y_pred, target_names = target_names))
```

```
                 precision    recall  f1-score   support

 offer_received       0.47      0.41      0.44     22886
   offer_viewed       0.23      0.13      0.17     17295
offer_completed       0.22      0.04      0.06     10141

      micro avg       0.38      0.24      0.30     50322
      macro avg       0.31      0.19      0.22     50322
   weighted avg       0.34      0.24      0.27     50322
    samples avg       0.13      0.13      0.13     50322
```

```
/Users/anateresaneto/opt/miniconda3/envs/my_env/lib/python3.9/site-
packages/sklearn/metrics/_classification.py:1248: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in samples with no
predicted labels. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/anateresaneto/opt/miniconda3/envs/my_env/lib/python3.9/site-
packages/sklearn/metrics/_classification.py:1248: UndefinedMetricWarning: Recall
and F-score are ill-defined and being set to 0.0 in samples with no true labels.
Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

AdaboostClassifier