Starbucks_Capstone_notebook-Nandini Submission

March 1, 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

Note: If you are using the workspace, you will need to go to the terminal and run the command `conda update pandas` before reading in the files. This is because the version of pandas in the workspace cannot read in the transcript.json file correctly, but the newest version of pandas can. You can access the termnal from the orange icon in the top left of this notebook.

You can see how to access the terminal and how the install works using the two images below. First you need to access the terminal:

Then you will want to run the above command:

Finally, when you enter back into the notebook (use the jupyter icon again), you should be able to run the below cell without any errors.

2.1 1.0 Analysis Setup

```
In [1]: #import all libraries
        import pandas as pd
        import numpy as np
        import math
        import json
        import datetime
        import pickle
        from sklearn.preprocessing import MultiLabelBinarizer # for one hot encoding
        import matplotlib.pyplot as plt
        import matplotlib.patches as mpatches
        from matplotlib.patches import Patch
        import pylab as pl
        import seaborn as sns
        import math
        % matplotlib inline
```

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

2.2 2. Data cleaning, data transformation and Feature extraction

Portfolio Dataset

```
In [104]: portfolio.head()
```

```
Out[104]:                        channels  difficulty  duration  \
          0       [email, mobile, social]          10         7
          1  [web, email, mobile, social]          10         5
          2          [web, email, mobile]           0         4
          3          [web, email, mobile]           5         7
          4                  [web, email]          20        10

                                           id     offer_type  reward
          0  ae264e3637204a6fb9bb56bc8210ddfd           bogo      10
          1  4d5c57ea9a6940dd891ad53e9dbe8da0           bogo      10
          2  3f207df678b143eea3cee63160fa8bed  informational       0
          3  9b98b8c7a33c4b65b9aebfe6a799e6d9           bogo       5
          4  0b1e1539f2cc45b7b9fa7c272da2e1d7       discount       5
```

```
In [105]: portfolio.shape
```

```
Out[105]: (10, 6)
```

```
In [106]: # total count of missing values
          print(portfolio.isnull().sum().sum())
          #no missing values
```

```
0
```

```
In [34]: #check for total type of offers
         portfolio['id'].nunique()
         #Total 10 offer ids in circulation
```

```
Out[34]: 10
```

```
In [107]: #check for duplicate rows
          portfolio[portfolio.duplicated(['id'], keep=False)]
```

```
Out[107]: Empty DataFrame
          Columns: [channels, difficulty, duration, id, offer_type, reward]
          Index: []
```

```
In [108]: def portfolio_transform(portfolio):
              '''
              Transforming the portfolio dataframe into the required format for our modelling an

              INPUT:
              portfolio - the portfolio dataframe to be transformed

              OUTPUT:
              portfolio_df - the transformed portfolio dataframe

              '''
              # change the duration from day to hour
              portfolio_df = portfolio.copy()
              portfolio_df['duration'] = portfolio_df['duration'] * 24

              # apply one hot encoding to channels column
              mlb = MultiLabelBinarizer()
              portfolio_df = portfolio_df.join(pd.DataFrame(mlb.fit_transform(portfolio_df.pop('
                                     columns=mlb.classes_,
                                     index=portfolio_df.index))

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

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

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

              return portfolio_df
```

```
In [109]: portfolio_df = portfolio_transform(portfolio)
          portfolio_df.head()
```

Out[109]:

	difficulty	duration	id	reward	email
0	10	168	ae264e3637204a6fb9bb56bc8210ddfd	10	1
1	10	120	4d5c57ea9a6940dd891ad53e9dbe8da0	10	1
2	0	96	3f207df678b143eea3cee63160fa8bed	0	1
3	5	168	9b98b8c7a33c4b65b9aebfe6a799e6d9	5	1
4	20	240	0b1e1539f2cc45b7b9fa7c272da2e1d7	5	1

	mobile	social	web	bogo	discount	informational
0	1	1	0	1	0	0
1	1	1	1	1	0	0
2	1	0	1	0	0	1
3	1	0	1	1	0	0
4	0	0	1	0	1	0

Profile Dataset

In [101]:
```
profile.head()
```

Out[101]:

	age	gender	id	income	member_since_days
1	55	F	0610b486422d4921ae7d2bf64640c50b	112000.0	1325
3	75	F	78afa995795e4d85b5d9ceeca43f5fef	100000.0	1392
5	68	M	e2127556f4f64592b11af22de27a7932	70000.0	1040
8	65	M	389bc3fa690240e798340f5a15918d5c	53000.0	1116
12	58	M	2eeac8d8feae4a8cad5a6af0499a211d	51000.0	1206

In [16]:
```
profile.shape
```

Out[16]: (17000, 5)

In [17]:
```
# total count of missing values
print(profile.isnull().sum().sum())
```

```
4350
```

No missing values in profile dataset

In [4]:
```
#missing values by column
profile.isnull().sum()
```

Out[4]:
```
age                 0
became_member_on    0
gender           2175
id                  0
income           2175
dtype: int64
```

Missing values in the gender and income column

In [10]:
```
#check for duplicate Customers
profile['id'].nunique()
#no duplicates found
```

Out[10]: 17000

In [ ]:
```
def profile_transform(profile):
    '''
    Transforming the profile dataframe into the required format for our modelling and an

    INPUT:
    profile - the portfolio dataframe to be transformed

    OUTPUT:
    profile - the transformed profile dataframe

    '''
    # drop all missing values since its only a small subset of dataset
    profile.dropna(inplace=True)

    # feature extraction the number of days since the user is a member of starbucks
    profile['member_since_days'] = datetime.datetime.today().date() - pd.to_datetime(pro
    profile['member_since_days'] = profile['member_since_days'].dt.days
     # drop the became_member_on column
    profile.drop(['became_member_on'], axis=1, inplace=True)

    return profile
```

In [110]:
```
profile_df = profile_transform(profile)
profile_df.head()
```

Out[110]:

	age	gender	id	income	member_since_days
1	55	F	0610b486422d4921ae7d2bf64640c50b	112000.0	1325
3	75	F	78afa995795e4d85b5d9ceeca43f5fef	100000.0	1392
5	68	M	e2127556f4f64592b11af22de27a7932	70000.0	1040
8	65	M	389bc3fa690240e798340f5a15918d5c	53000.0	1116
12	58	M	2eeac8d8feae4a8cad5a6af0499a211d	51000.0	1206

In [111]:
```
profile_df.describe()
```

Out[111]:

	age	income	member_since_days
count	14825.000000	14825.000000	14825.000000
mean	54.393524	65404.991568	1471.478988
std	17.383705	21598.299410	419.205158
min	18.000000	30000.000000	949.000000
25%	42.000000	49000.000000	1157.000000
50%	55.000000	64000.000000	1307.000000
75%	66.000000	80000.000000	1746.000000
max	101.000000	120000.000000	2772.000000

Transcript Dataset

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

Out[5]:            event                            person  time  \
        0  offer received  78afa995795e4d85b5d9ceeca43f5fef     0
        1  offer received  a03223e636434f42ac4c3df47e8bac43     0
        2  offer received  e2127556f4f64592b11af22de27a7932     0
        3  offer received  8ec6ce2a7e7949b1bf142def7d0e0586     0
        4  offer received  68617ca6246f4fbc85e91a2a49552598     0

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

In [11]: transcript.shape

Out[11]: (306534, 4)

In [9]: transcript['event'].unique()

Out[9]: array(['offer received', 'offer viewed', 'transaction', 'offer completed'], dtype=object

In [13]: #Check missing values
         transcript.isnull().sum()

Out[13]: event     0
         person    0
         time      0
         value     0
         dtype: int64

In [14]: # explore the transcript records for one user
         transcript[transcript['person']=='78afa995795e4d85b5d9ceeca43f5fef']

Out[14]:                 event                            person  time  \
         0       offer received  78afa995795e4d85b5d9ceeca43f5fef     0
         15561     offer viewed  78afa995795e4d85b5d9ceeca43f5fef     6
         47582      transaction  78afa995795e4d85b5d9ceeca43f5fef   132
         47583  offer completed  78afa995795e4d85b5d9ceeca43f5fef   132
         49502      transaction  78afa995795e4d85b5d9ceeca43f5fef   144
         53176   offer received  78afa995795e4d85b5d9ceeca43f5fef   168
         85291     offer viewed  78afa995795e4d85b5d9ceeca43f5fef   216
         87134      transaction  78afa995795e4d85b5d9ceeca43f5fef   222
         92104      transaction  78afa995795e4d85b5d9ceeca43f5fef   240
         141566     transaction  78afa995795e4d85b5d9ceeca43f5fef   378
```

```
150598   offer received  78afa995795e4d85b5d9ceeca43f5fef   408
163375     offer viewed  78afa995795e4d85b5d9ceeca43f5fef   408
201572   offer received  78afa995795e4d85b5d9ceeca43f5fef   504
218393      transaction  78afa995795e4d85b5d9ceeca43f5fef   510
218394  offer completed  78afa995795e4d85b5d9ceeca43f5fef   510
218395  offer completed  78afa995795e4d85b5d9ceeca43f5fef   510
230412      transaction  78afa995795e4d85b5d9ceeca43f5fef   534
262138     offer viewed  78afa995795e4d85b5d9ceeca43f5fef   582

                                                     value
0        {'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}
15561    {'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}
47582                                  {'amount': 19.89}
47583   {'offer_id': '9b98b8c7a33c4b65b9aebfe6a799e6d9...
49502                                  {'amount': 17.78}
53176    {'offer id': '5a8bc65990b245e5a138643cd4eb9837'}
85291    {'offer id': '5a8bc65990b245e5a138643cd4eb9837'}
87134                                  {'amount': 19.67}
92104                                  {'amount': 29.72}
141566                                 {'amount': 23.93}
150598   {'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}
163375   {'offer id': 'ae264e3637204a6fb9bb56bc8210ddfd'}
201572   {'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}
218393                                 {'amount': 21.72}
218394  {'offer_id': 'ae264e3637204a6fb9bb56bc8210ddfd...
218395  {'offer_id': 'f19421c1d4aa40978ebb69ca19b0e20d...
230412                                 {'amount': 26.56}
262138   {'offer id': 'f19421c1d4aa40978ebb69ca19b0e20d'}
```

In [11]:
```python
def transcript_transform(transcript):
    '''
    Transforming the profile dataframe into the required format for our modelling and a

    INPUT:
    transcript - the transcript dataframe to be transformed

    OUTPUT:
    transcript - the transformed transcript dataframe

    '''
    # extract the rows that are related to offer action (e.g. 'offer received', 'offer
    list_of_values = ['offer received', 'offer viewed', 'offer completed']

    transcript =  transcript[transcript['event'].isin(list_of_values)]

    # extract the offer id from value column
    transcript['offer_id'] = transcript['value'].apply(lambda x: x['offer id'] if ('off
```

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

    return transcript
```

In [12]: transcript_df = transcript_transform(transcript)

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:18: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
/opt/conda/lib/python3.6/site-packages/pandas/core/frame.py:3697: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  errors=errors)
```

In [13]: transcript_df.head()

Out[13]:

	event	person	time	\
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	0	
1	offer received	a03223e636434f42ac4c3df47e8bac43	0	
2	offer received	e2127556f4f64592b11af22de27a7932	0	
3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	0	
4	offer received	68617ca6246f4fbc85e91a2a49552598	0	

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

In [13]: transcript_df.describe()

Out[13]:

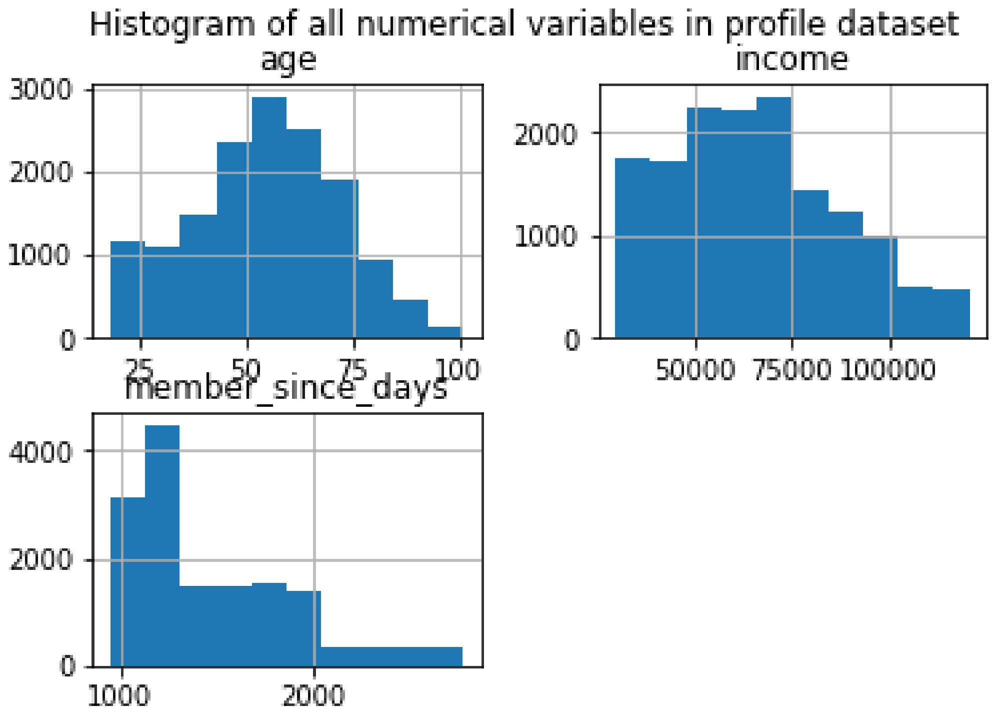
	time
count	167581.000000
mean	353.778412
std	198.301287
min	0.000000
25%	168.000000
50%	408.000000
75%	510.000000
max	714.000000

2.3 3. Exploratory Data Analysis

Profile Dataset

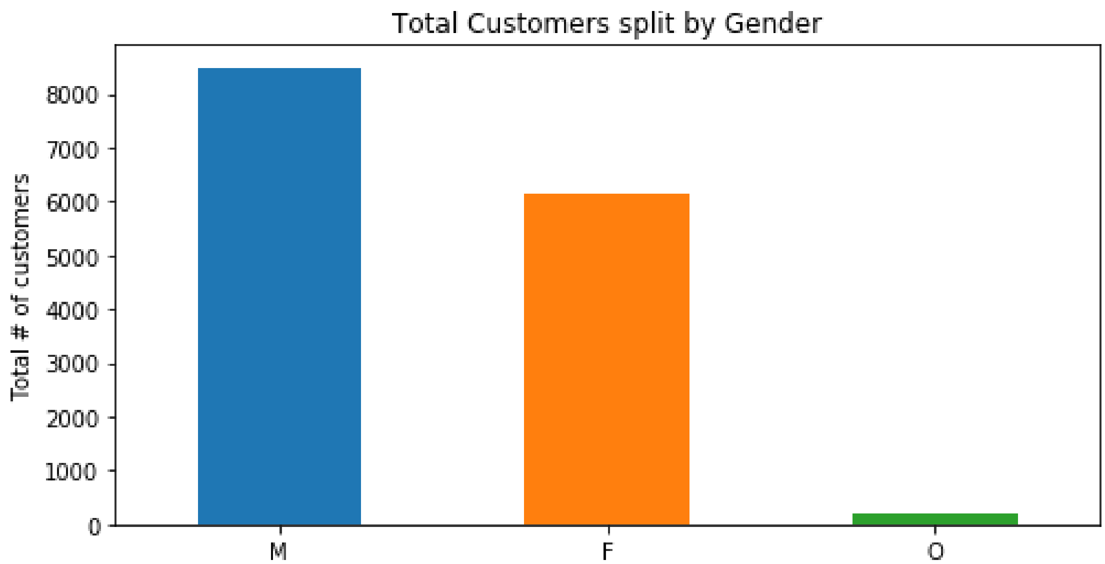
In [59]:
```
#Make histogram of all numerical variables
axes = profile_df.hist()
pl.suptitle("Histogram of all numerical variables in profile dataset")
```

Out[59]:
```
Text(0.5,0.98,'Histogram of all numerical variables in profile dataset')
```



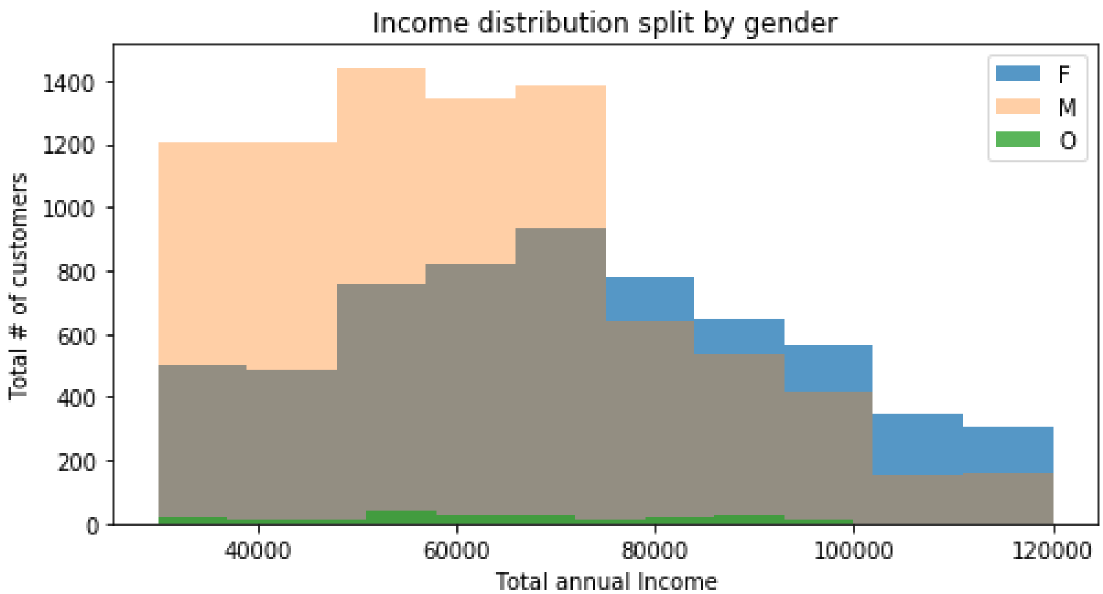
The distributions shows the following three things about our customer profile * Most customers are in the middle to older age range * Annual income of Starbucks customers is majorly $100000 * Most customers take >1000 and <1250 days before they become a member

In [84]:
```
#plotting gender distribution
fig, ax = plt.subplots(figsize = (8,4))
profile_df.gender.value_counts().plot(kind='bar', ax=ax)
ax.set_xticklabels(ax.get_xticklabels(), rotation=0)
ax.set_title('Total Customers split by Gender')
ax.set_ylabel('Total # of customers')
plt.show ()
```



The dataset contains higher percentage of Male customers as opposed to female/other.

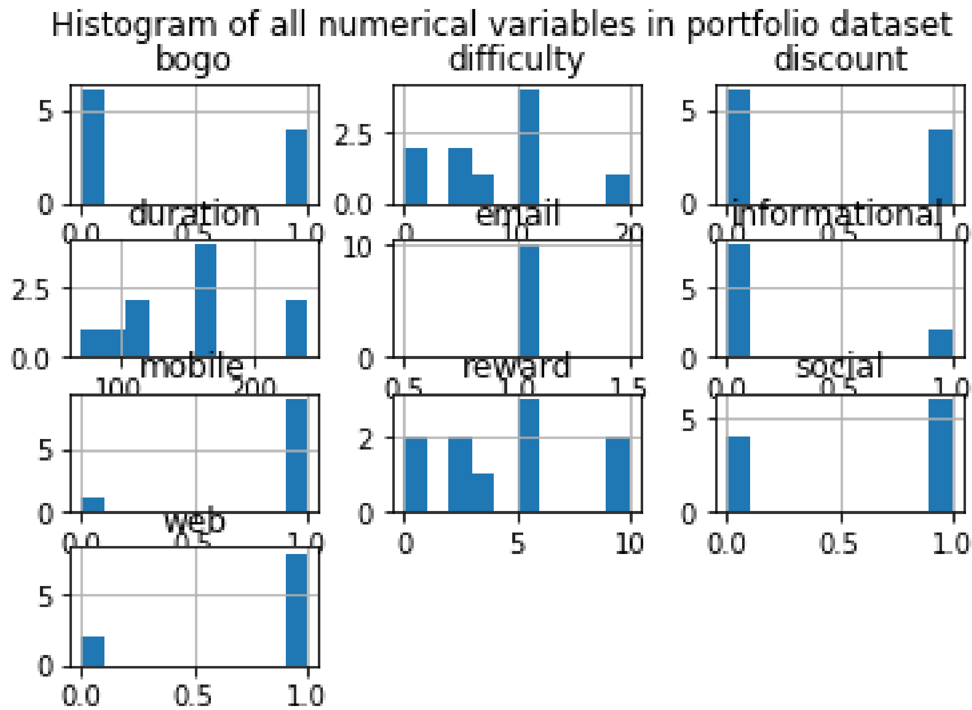
```
In [86]: # plot income distribution histogram
         fig, ax = plt.subplots(figsize = (8,4))

         ax.hist(profile_df[profile_df.gender == 'F']['income'], alpha=0.76, label='F')
         ax.hist(profile_df[profile_df.gender == 'M']['income'], alpha=0.37, label='M')
         ax.hist(profile_df[profile_df.gender == 'O']['income'], alpha=0.78, label='O')
         ax.set_xlabel('Total annual Income')
         ax.set_ylabel('Total # of customers')
         ax.set_title('Income distribution split by gender')
         ax.legend()
         plt.show ()
```



Male customers have have a left skewed income distribution of <=$80000 whereas female customer's income seems to normally distributed across the range

Portfolio Dataset

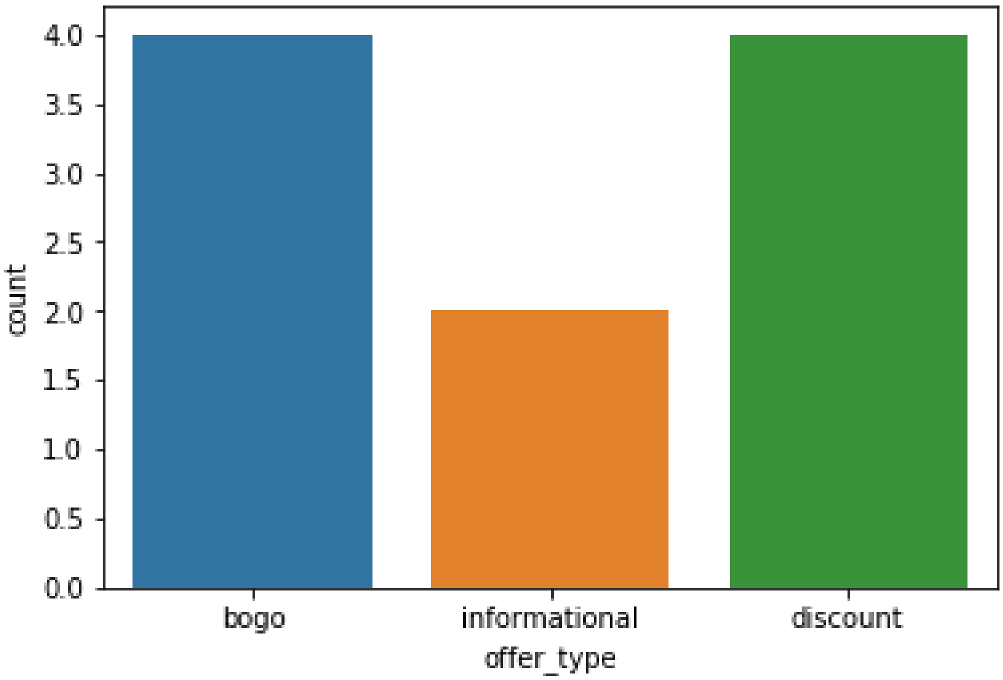
```
In [33]: #Make histogram of all numerical variables
         axes = portfolio_df.hist()
         pl.suptitle("Histogram of all numerical variables in portfolio dataset")

Out[33]: Text(0.5,0.98,'Histogram of all numerical variables in portfolio dataset')
```



This view is not highly insightful, however we can see that difficulty of 10 and reward of 5 seems to be the most commonly occuring ones in the offers

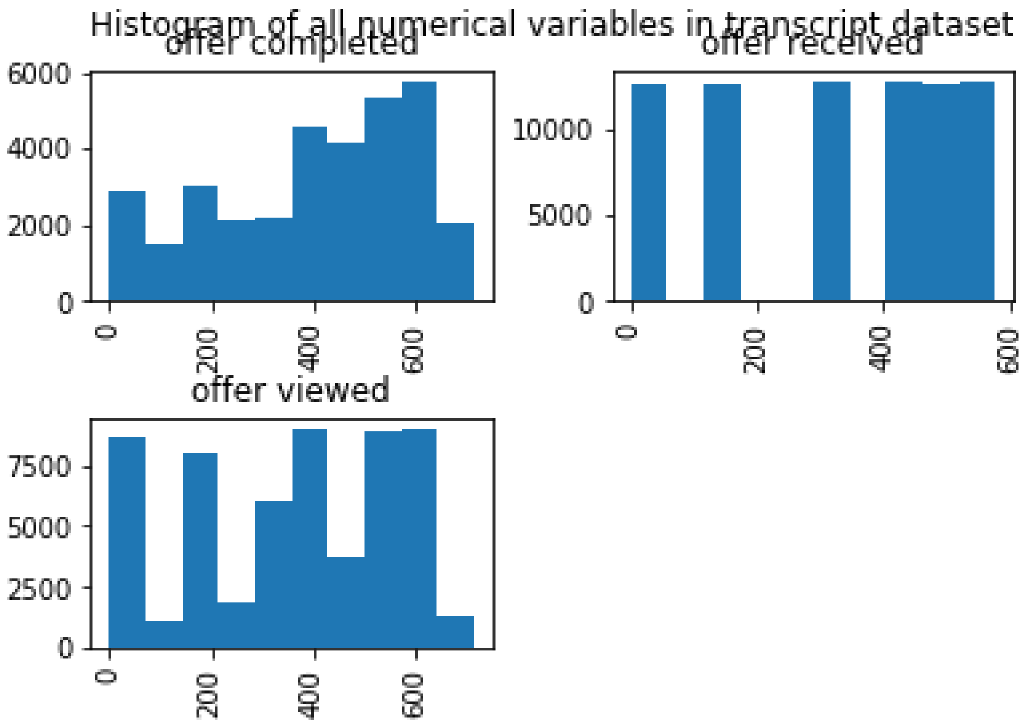
In [114]:
```
#checking distribution of events in the dataframe
sns.countplot('offer_type', data= portfolio)
```

Out[114]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f868efb1550>
```



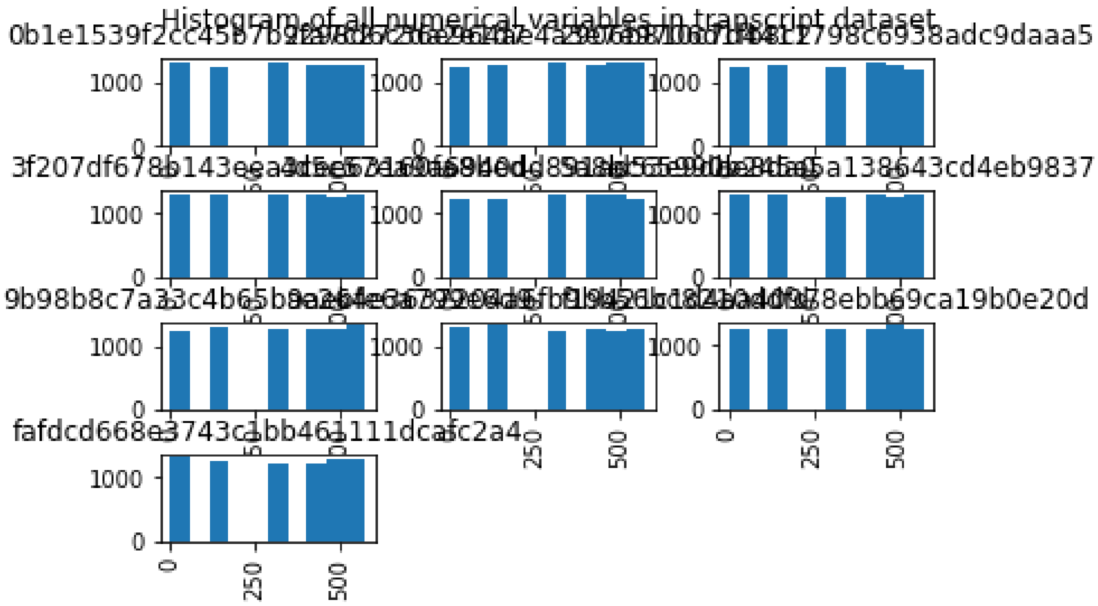
Offer types are dominated by BOGO and discount.
Transcript dataset

```
In [37]: #Make histogram of all numerical variables
         axes = transcript_df['time'].hist(by=transcript_df['event'])
         pl.suptitle("Histogram of all numerical variables in transcript dataset")

Out[37]: Text(0.5,0.98,'Histogram of all numerical variables in transcript dataset')
```



Based on the above charts we can see that there are specific times in which offers are recieved i.e. Starbucks sends out these offers at once to all relevant customers. However, there is so specific time when the offers maybe viewed and completed as expected.

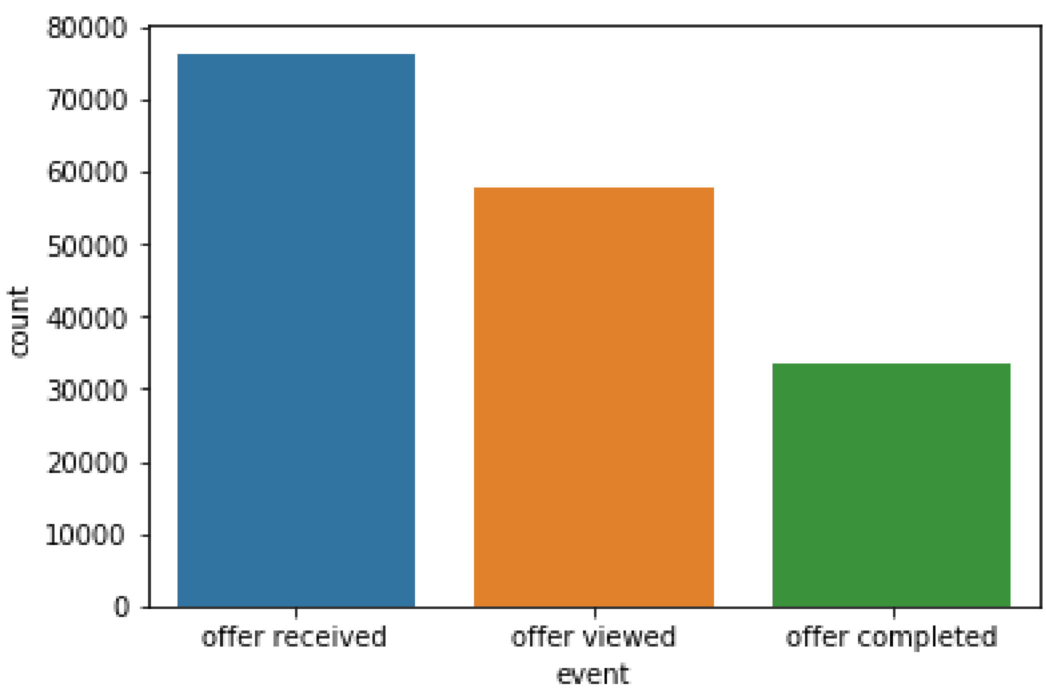
```
In [40]: axes = transcript_df['time'].hist(by=transcript_df[transcript_df['event']=='offer recei
         pl.suptitle("Histogram of time when a specfic type of offer is sent out")

Out[40]: Text(0.5,0.98,'Histogram of all numerical variables in transcript dataset')
```



As is expected there isnt a specific time for any particular type of offer to be sent out.

```
In [90]: #checking distribution of events in the dataframe
         sns.countplot('event', data= transcript_df)
```

```
Out[90]: <matplotlib.axes._subplots.AxesSubplot at 0x7f868f015080>
```



The offer recieved,viewed and completed follow the expected trend i.e more offers are sent out than will be viewed or completed.

2.4 4. Data modelling

In order to build a recomendation engine, we can use FunkSVD algorithm. The dataset needs to be in user-item matrix format for that purposes. Following functions will help further transform the datasets

```
In [53]: def create_user_item_matrix(offers_given, filename):
             '''
             Return the user item matrix that indicate the number of offer complete of a particu

             INPUT:
             offer - a cleaned transcript dataframe
             filename(string) - the file name that save the user item matrix

             OUTPUT:
             user_item_matrix - the user item matrix which
                 - row is user
                 - column is offer
                 - value is the number of offer complete by the user (NaN means no offer given)

             '''
             # create an empty user item matrix
             user_item_matrix = offers_given.groupby(['person', 'offer_id'])['event'].agg(lambda
             # Retaining only bogo and discount offers first and dropping all else for simplicit
             user_item_matrix.drop(list(portfolio[portfolio['offer_type']=='informational']['id'

             for offer_id in user_item_matrix.columns:
                 print("Processing Offer: ", offer_id)
                 num = 0
                 for person in user_item_matrix.index:
                     num += 1
                     if num % 5000 == 0:
                         print("finished upto #:", num, 'persons')
                     events = []
                     for event in offers_given[(offers_given['offer_id']==offer_id) & (offers_gi
                         events.append(event)
                     if len(events) >= 3:
                         user_item_matrix.loc[person, offer_id] = 0
                         for i in range(len(events)-2):
                             # check that transaction sequence is offer received -> offer viewed
                             # Only if its in that order we assume the offer was successfully ac
                             if (events[i] == 'offer received') & (events[i+1] == 'offer viewed'
                                 user_item_matrix.loc[person, offer_id] += 1
```

```
                elif len(events) > 0:
                    user_item_matrix.loc[person, offer_id] = 0

        # store the large martix into file
        fh = open(filename, 'wb')
        pickle.dump(user_item_matrix,fh)
        fh.close()

        return user_item_matrix
```

In [19]:
```
#create User item matrix of customers and offers they accept
all_df = create_user_item_matrix(transcript_df, 'user_item_matrix.p')
```

```
Processing Offer:  0b1e1539f2cc45b7b9fa7c272da2e1d7
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  2298d6c36e964ae4a3e7e9706d1fb8c2
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  2906b810c7d4411798c6938adc9daaa5
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  4d5c57ea9a6940dd891ad53e9dbe8da0
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  9b98b8c7a33c4b65b9aebfe6a799e6d9
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  ae264e3637204a6fb9bb56bc8210ddfd
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  f19421c1d4aa40978ebb69ca19b0e20d
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  fafdcd668e3743c1bb461111dcafc2a4
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
```

In [20]:
```
all_df.head()
```

```
Out[20]: offer_id                          0b1e1539f2cc45b7b9fa7c272da2e1d7  \
         person
         0009655768c64bdeb2e877511632db8f                               NaN
         00116118485d4dfda04fdbaba9a87b5c                               NaN
         0011e0d4e6b944f998e987f904e8c1e5                               1.0
         0020c2b971eb4e9188eac86d93036a77                               NaN
         0020ccbbb6d84e358d3414a3ff76cffd                               NaN

         offer_id                          2298d6c36e964ae4a3e7e9706d1fb8c2  \
         person
         0009655768c64bdeb2e877511632db8f                               NaN
         00116118485d4dfda04fdbaba9a87b5c                               NaN
         0011e0d4e6b944f998e987f904e8c1e5                               1.0
         0020c2b971eb4e9188eac86d93036a77                               NaN
         0020ccbbb6d84e358d3414a3ff76cffd                               1.0

         offer_id                          2906b810c7d4411798c6938adc9daaa5  \
         person
         0009655768c64bdeb2e877511632db8f                               0.0
         00116118485d4dfda04fdbaba9a87b5c                               NaN
         0011e0d4e6b944f998e987f904e8c1e5                               NaN
         0020c2b971eb4e9188eac86d93036a77                               NaN
         0020ccbbb6d84e358d3414a3ff76cffd                               NaN

         offer_id                          4d5c57ea9a6940dd891ad53e9dbe8da0  \
         person
         0009655768c64bdeb2e877511632db8f                               NaN
         00116118485d4dfda04fdbaba9a87b5c                               NaN
         0011e0d4e6b944f998e987f904e8c1e5                               NaN
         0020c2b971eb4e9188eac86d93036a77                               1.0
         0020ccbbb6d84e358d3414a3ff76cffd                               NaN

         offer_id                          9b98b8c7a33c4b65b9aebfe6a799e6d9  \
         person
         0009655768c64bdeb2e877511632db8f                               NaN
         00116118485d4dfda04fdbaba9a87b5c                               NaN
         0011e0d4e6b944f998e987f904e8c1e5                               1.0
         0020c2b971eb4e9188eac86d93036a77                               NaN
         0020ccbbb6d84e358d3414a3ff76cffd                               1.0

         offer_id                          ae264e3637204a6fb9bb56bc8210ddfd  \
         person
         0009655768c64bdeb2e877511632db8f                               NaN
         00116118485d4dfda04fdbaba9a87b5c                               NaN
         0011e0d4e6b944f998e987f904e8c1e5                               NaN
         0020c2b971eb4e9188eac86d93036a77                               0.0
         0020ccbbb6d84e358d3414a3ff76cffd                               NaN
```

```
offer_id                          f19421c1d4aa40978ebb69ca19b0e20d  \
person
0009655768c64bdeb2e877511632db8f                               0.0
00116118485d4dfda04fdbaba9a87b5c                               0.0
0011e0d4e6b944f998e987f904e8c1e5                               NaN
0020c2b971eb4e9188eac86d93036a77                               NaN
0020ccbbb6d84e358d3414a3ff76cffd                               1.0

offer_id                          fafdcd668e3743c1bb461111dcafc2a4
person
0009655768c64bdeb2e877511632db8f                               0.0
00116118485d4dfda04fdbaba9a87b5c                               NaN
0011e0d4e6b944f998e987f904e8c1e5                               NaN
0020c2b971eb4e9188eac86d93036a77                               1.0
0020ccbbb6d84e358d3414a3ff76cffd                               NaN
```

In [55]:
```
#Function to split dataset in training and testing subsets
def user_item_train_test_split (transcript_df, training_perc=0.7):
    """Function that prepares train and test user_item_matrices out of transcript datas

    INPUT:
    1.  dataframe to split into training and testing datasets
    2.  training dataset size percentage, default = 0.7

    OUTPUT:
    1.  train dataframe
    2.  test dataframe
    3.  train user_item_matrix
    4.  test user_item_matrix

    """

     #saving a dataframe copy to work with
    transcript_dfcopy = transcript_df.copy()

    training_size= math.ceil(transcript_dfcopy.shape[0]*training_perc)
    testing_size= transcript_dfcopy.shape[0]-training_size

    training_df = transcript_dfcopy.head(training_size)
    test_df = transcript_dfcopy.iloc[training_size:training_size+testing_size]

    #converting both into user_item_matrix format
    print('Preparing Training matrix')
    train_matrix = create_user_item_matrix(training_df, 'train_df.p')
    print('Preparing Testing matrix')
    test_matrix = create_user_item_matrix(test_df, 'test_df.p')

    return training_df,test_df,train_matrix, test_matrix
```

```
In [56]: training_df,test_df,train_matrix, test_matrix  =user_item_train_test_split(transcript_d
```

```
Preparing Training matrix
Processing Offer:  0b1e1539f2cc45b7b9fa7c272da2e1d7
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  2298d6c36e964ae4a3e7e9706d1fb8c2
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  2906b810c7d4411798c6938adc9daaa5
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  4d5c57ea9a6940dd891ad53e9dbe8da0
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  9b98b8c7a33c4b65b9aebfe6a799e6d9
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  ae264e3637204a6fb9bb56bc8210ddfd
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  f19421c1d4aa40978ebb69ca19b0e20d
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  fafdcd668e3743c1bb461111dcafc2a4
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Preparing Testing matrix
Processing Offer:  0b1e1539f2cc45b7b9fa7c272da2e1d7
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  2298d6c36e964ae4a3e7e9706d1fb8c2
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  2906b810c7d4411798c6938adc9daaa5
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
```

```
Processing Offer:  4d5c57ea9a6940dd891ad53e9dbe8da0
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  9b98b8c7a33c4b65b9aebfe6a799e6d9
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  ae264e3637204a6fb9bb56bc8210ddfd
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  f19421c1d4aa40978ebb69ca19b0e20d
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
Processing Offer:  fafdcd668e3743c1bb461111dcafc2a4
finished upto #: 5000 persons
finished upto #: 10000 persons
finished upto #: 15000 persons
```

In [57]:
```
train_matrix.head()
```

Out[57]:
```
offer_id                          0b1e1539f2cc45b7b9fa7c272da2e1d7  \
person
0009655768c64bdeb2e877511632db8f                               NaN
00116118485d4dfda04fdbaba9a87b5c                               NaN
0011e0d4e6b944f998e987f904e8c1e5                               0.0
0020c2b971eb4e9188eac86d93036a77                               NaN
0020ccbbb6d84e358d3414a3ff76cffd                               NaN

offer_id                          2298d6c36e964ae4a3e7e9706d1fb8c2  \
person
0009655768c64bdeb2e877511632db8f                               NaN
00116118485d4dfda04fdbaba9a87b5c                               NaN
0011e0d4e6b944f998e987f904e8c1e5                               1.0
0020c2b971eb4e9188eac86d93036a77                               NaN
0020ccbbb6d84e358d3414a3ff76cffd                               1.0

offer_id                          2906b810c7d4411798c6938adc9daaa5  \
person
0009655768c64bdeb2e877511632db8f                               NaN
00116118485d4dfda04fdbaba9a87b5c                               NaN
0011e0d4e6b944f998e987f904e8c1e5                               NaN
0020c2b971eb4e9188eac86d93036a77                               NaN
0020ccbbb6d84e358d3414a3ff76cffd                               NaN
```

```
offer_id                          4d5c57ea9a6940dd891ad53e9dbe8da0  \
person
0009655768c64bdeb2e877511632db8f                               NaN
00116118485d4dfda04fdbaba9a87b5c                               NaN
0011e0d4e6b944f998e987f904e8c1e5                               NaN
0020c2b971eb4e9188eac86d93036a77                               0.0
0020ccbbb6d84e358d3414a3ff76cffd                               NaN

offer_id                          9b98b8c7a33c4b65b9aebfe6a799e6d9  \
person
0009655768c64bdeb2e877511632db8f                               NaN
00116118485d4dfda04fdbaba9a87b5c                               NaN
0011e0d4e6b944f998e987f904e8c1e5                               0.0
0020c2b971eb4e9188eac86d93036a77                               NaN
0020ccbbb6d84e358d3414a3ff76cffd                               0.0

offer_id                          ae264e3637204a6fb9bb56bc8210ddfd  \
person
0009655768c64bdeb2e877511632db8f                               NaN
00116118485d4dfda04fdbaba9a87b5c                               NaN
0011e0d4e6b944f998e987f904e8c1e5                               NaN
0020c2b971eb4e9188eac86d93036a77                               0.0
0020ccbbb6d84e358d3414a3ff76cffd                               NaN

offer_id                          f19421c1d4aa40978ebb69ca19b0e20d  \
person
0009655768c64bdeb2e877511632db8f                               0.0
00116118485d4dfda04fdbaba9a87b5c                               0.0
0011e0d4e6b944f998e987f904e8c1e5                               NaN
0020c2b971eb4e9188eac86d93036a77                               NaN
0020ccbbb6d84e358d3414a3ff76cffd                               1.0

offer_id                          fafdcd668e3743c1bb461111dcafc2a4
person
0009655768c64bdeb2e877511632db8f                               0.0
00116118485d4dfda04fdbaba9a87b5c                               NaN
0011e0d4e6b944f998e987f904e8c1e5                               NaN
0020c2b971eb4e9188eac86d93036a77                               1.0
0020ccbbb6d84e358d3414a3ff76cffd                               NaN
```

In [14]:
```
# Data checkpoint to read user matrices when needed
# all_df = pd.read_pickle('user_item_matrix.p')
# train_matrix = pd.read_pickle('train_df.p')
# test_matrix = pd.read_pickle('train_df.p')
```

In [58]:
```
#Function implementing FunkSVD
def FunkSVD(user_item_matrix, latent_features=4, learning_rate=0.0001, iters=100):
    '''
```

```
    This function performs matrix factorization using a basic form of FunkSVD with no r

    INPUT:
    user_mat - (numpy array) a matrix with users as rows, offers as columns, and comple
    latent_features - (int) the number of latent features used
    learning_rate - (float) the learning rate
    iters - (int) the number of iterations

    OUTPUT:
    user_mat - (numpy array) a user by latent feature matrix
    movie_mat - (numpy array) a latent feature by movie matrix
    '''

    # Set up useful values to be used through the rest of the function
    n_users = user_item_matrix.shape[0]
    n_offers = user_item_matrix.shape[1]
    num_offers = np.count_nonzero(~np.isnan(user_item_matrix))

    # initialize the user and movie matrices with random values
    user_mat = np.random.rand(n_users, latent_features)
    offer_mat = np.random.rand(latent_features, n_offers)

    # initialize sse at 0 for first iteration
    sse_accum = 0

    # header for running results
    print("Optimizaiton Statistics")
    print("Iterations | Mean Squared Error ")

    # for each iteration
    for iteration in range(iters):

        # update our sse
        old_sse = sse_accum
        sse_accum = 0

        # For each user-offer pair
        for i in range(n_users):
            for j in range(n_offers):

                # if the offer was completed
                if user_item_matrix[i, j] > 0:

                    # compute the error as the actual minus the dot product of the user
                    diff = user_item_matrix[i, j] - np.dot(user_mat[i, :], offer_mat[:,

                    # Keep track of the sum of squared errors for the matrix
                    sse_accum += diff**2
```

```
                    # update the values in each matrix in the direction of the gradient
                    for k in range(latent_features):
                        user_mat[i, k] += learning_rate * (2*diff*offer_mat[k, j])
                        offer_mat[k, j] += learning_rate * (2*diff*user_mat[i, k])

            # print results for iteration
            print("%d \t\t %f" % (iteration+1, sse_accum / num_offers))

        return user_mat, offer_mat
```

In [59]:
```
#create numpy array of training matrix
np_train=np.matrix(train_matrix)
```

In [60]:
```
# Fit FunkSVD with the specified hyper parameters to the training data
user_mat_20, offer_mat_20 = FunkSVD(np_train, latent_features=20, learning_rate=0.005,
```

```
Optimizaiton Statistics
Iterations | Mean Squared Error
1                  0.079313
2                  0.029744
3                  0.028501
4                  0.028176
5                  0.027991
6                  0.027834
7                  0.027686
8                  0.027540
9                  0.027395
10                  0.027252
11                  0.027109
12                  0.026968
13                  0.026827
14                  0.026687
15                  0.026548
16                  0.026410
17                  0.026273
18                  0.026137
19                  0.026001
20                  0.025867
21                  0.025733
22                  0.025600
23                  0.025468
24                  0.025336
25                  0.025206
26                  0.025076
27                  0.024947
28                  0.024819
29                  0.024692
```

30	0.024565
31	0.024439
32	0.024314
33	0.024190
34	0.024066
35	0.023943
36	0.023821
37	0.023700
38	0.023579
39	0.023459
40	0.023340
41	0.023221
42	0.023103
43	0.022986
44	0.022869
45	0.022754
46	0.022638
47	0.022524
48	0.022410
49	0.022297
50	0.022184
51	0.022072
52	0.021961
53	0.021851
54	0.021740
55	0.021631
56	0.021522
57	0.021414
58	0.021307
59	0.021200
60	0.021093
61	0.020987
62	0.020882
63	0.020777
64	0.020673
65	0.020570
66	0.020467
67	0.020364
68	0.020263
69	0.020161
70	0.020061
71	0.019960
72	0.019861
73	0.019761
74	0.019663
75	0.019565
76	0.019467
77	0.019370

78	0.019273
79	0.019177
80	0.019082
81	0.018986
82	0.018892
83	0.018798
84	0.018704
85	0.018611
86	0.018518
87	0.018426
88	0.018334
89	0.018243
90	0.018152
91	0.018061
92	0.017971
93	0.017882
94	0.017793
95	0.017704
96	0.017616
97	0.017528
98	0.017440
99	0.017353
100	0.017267
101	0.017181
102	0.017095
103	0.017010
104	0.016925
105	0.016840
106	0.016756
107	0.016672
108	0.016589
109	0.016506
110	0.016424
111	0.016341
112	0.016260
113	0.016178
114	0.016097
115	0.016016
116	0.015936
117	0.015856
118	0.015776
119	0.015697
120	0.015618
121	0.015540
122	0.015461
123	0.015384
124	0.015306
125	0.015229

126	0.015152
127	0.015076
128	0.014999
129	0.014924
130	0.014848
131	0.014773
132	0.014698
133	0.014624
134	0.014549
135	0.014476
136	0.014402
137	0.014329
138	0.014256
139	0.014183
140	0.014111
141	0.014039
142	0.013967
143	0.013896
144	0.013824
145	0.013754
146	0.013683
147	0.013613
148	0.013543
149	0.013473
150	0.013404
151	0.013335
152	0.013266
153	0.013197
154	0.013129
155	0.013061
156	0.012993
157	0.012926
158	0.012859
159	0.012792
160	0.012725
161	0.012659
162	0.012593
163	0.012527
164	0.012461
165	0.012396
166	0.012331
167	0.012266
168	0.012202
169	0.012137
170	0.012073
171	0.012010
172	0.011946
173	0.011883

174	0.011820
175	0.011757
176	0.011694
177	0.011632
178	0.011570
179	0.011508
180	0.011447
181	0.011386
182	0.011324
183	0.011264
184	0.011203
185	0.011143
186	0.011083
187	0.011023
188	0.010963
189	0.010904
190	0.010844
191	0.010785
192	0.010727
193	0.010668
194	0.010610
195	0.010552
196	0.010494
197	0.010437
198	0.010379
199	0.010322
200	0.010265
201	0.010208
202	0.010152
203	0.010096
204	0.010040
205	0.009984
206	0.009928
207	0.009873
208	0.009818
209	0.009763
210	0.009708
211	0.009653
212	0.009599
213	0.009545
214	0.009491
215	0.009438
216	0.009384
217	0.009331
218	0.009278
219	0.009225
220	0.009172
221	0.009120

```
222                     0.009068
223                     0.009016
224                     0.008964
225                     0.008913
226                     0.008861
227                     0.008810
228                     0.008759
229                     0.008708
230                     0.008658
231                     0.008607
232                     0.008557
233                     0.008507
234                     0.008458
235                     0.008408
236                     0.008359
237                     0.008310
238                     0.008261
239                     0.008212
240                     0.008164
241                     0.008115
242                     0.008067
243                     0.008019
244                     0.007972
245                     0.007924
246                     0.007877
247                     0.007830
248                     0.007783
249                     0.007736
250                     0.007689
```

In [61]:
```
# Test for the best number of latent feature. (with latent features 10)
user_mat_15, offer_mat_15 = FunkSVD(np_train, latent_features=15, learning_rate=0.005,
```

```
Optimizaiton Statistics
Iterations | Mean Squared Error
1                   0.061120
2                   0.031322
3                   0.030512
4                   0.030224
5                   0.029999
6                   0.029786
7                   0.029576
8                   0.029369
9                   0.029164
10                   0.028961
11                   0.028759
12                   0.028560
```

13	0.028362
14	0.028166
15	0.027972
16	0.027779
17	0.027589
18	0.027400
19	0.027212
20	0.027027
21	0.026843
22	0.026661
23	0.026480
24	0.026301
25	0.026124
26	0.025948
27	0.025774
28	0.025602
29	0.025431
30	0.025261
31	0.025093
32	0.024927
33	0.024761
34	0.024598
35	0.024436
36	0.024275
37	0.024116
38	0.023958
39	0.023801
40	0.023646
41	0.023493
42	0.023340
43	0.023189
44	0.023039
45	0.022891
46	0.022744
47	0.022598
48	0.022453
49	0.022310
50	0.022168
51	0.022027
52	0.021887
53	0.021748
54	0.021611
55	0.021475
56	0.021340
57	0.021206
58	0.021073
59	0.020942
60	0.020811

61	0.020682
62	0.020553
63	0.020426
64	0.020300
65	0.020175
66	0.020051
67	0.019928
68	0.019806
69	0.019685
70	0.019565
71	0.019446
72	0.019328
73	0.019211
74	0.019095
75	0.018980
76	0.018866
77	0.018752
78	0.018640
79	0.018529
80	0.018418
81	0.018309
82	0.018200
83	0.018092
84	0.017985
85	0.017879
86	0.017774
87	0.017669
88	0.017566
89	0.017463
90	0.017361
91	0.017260
92	0.017159
93	0.017060
94	0.016961
95	0.016863
96	0.016765
97	0.016669
98	0.016573
99	0.016478
100	0.016384
101	0.016290
102	0.016197
103	0.016105
104	0.016014
105	0.015923
106	0.015833
107	0.015744
108	0.015655

109	0.015567
110	0.015480
111	0.015393
112	0.015307
113	0.015221
114	0.015137
115	0.015052
116	0.014969
117	0.014886
118	0.014804
119	0.014722
120	0.014641
121	0.014560
122	0.014480
123	0.014401
124	0.014322
125	0.014244
126	0.014166
127	0.014089
128	0.014013
129	0.013937
130	0.013861
131	0.013786
132	0.013712
133	0.013638
134	0.013565
135	0.013492
136	0.013419
137	0.013348
138	0.013276
139	0.013205
140	0.013135
141	0.013065
142	0.012996
143	0.012927
144	0.012858
145	0.012790
146	0.012723
147	0.012656
148	0.012589
149	0.012523
150	0.012457
151	0.012392
152	0.012327
153	0.012262
154	0.012198
155	0.012135
156	0.012072

157	0.012009
158	0.011946
159	0.011884
160	0.011823
161	0.011762
162	0.011701
163	0.011641
164	0.011580
165	0.011521
166	0.011462
167	0.011403
168	0.011344
169	0.011286
170	0.011228
171	0.011171
172	0.011114
173	0.011057
174	0.011001
175	0.010944
176	0.010889
177	0.010833
178	0.010778
179	0.010724
180	0.010669
181	0.010615
182	0.010562
183	0.010508
184	0.010455
185	0.010402
186	0.010350
187	0.010298
188	0.010246
189	0.010194
190	0.010143
191	0.010092
192	0.010041
193	0.009991
194	0.009941
195	0.009891
196	0.009841
197	0.009792
198	0.009743
199	0.009695
200	0.009646
201	0.009598
202	0.009550
203	0.009502
204	0.009455

205	0.009408
206	0.009361
207	0.009314
208	0.009268
209	0.009222
210	0.009176
211	0.009131
212	0.009085
213	0.009040
214	0.008995
215	0.008951
216	0.008906
217	0.008862
218	0.008818
219	0.008774
220	0.008731
221	0.008688
222	0.008644
223	0.008602
224	0.008559
225	0.008517
226	0.008474
227	0.008432
228	0.008391
229	0.008349
230	0.008308
231	0.008267
232	0.008226
233	0.008185
234	0.008145
235	0.008104
236	0.008064
237	0.008024
238	0.007984
239	0.007945
240	0.007905
241	0.007866
242	0.007827
243	0.007789
244	0.007750
245	0.007711
246	0.007673
247	0.007635
248	0.007597
249	0.007560
250	0.007522

```
In [62]: # Test for the best number of latent feature. (with latent features 10)
         user_mat_10, offer_mat_10 = FunkSVD(np_train, latent_features=10, learning_rate=0.005,
```

```
Optimizaiton Statistics
Iterations | Mean Squared Error
1                  0.050931
2                  0.034200
3                  0.033361
4                  0.032943
5                  0.032580
6                  0.032229
7                  0.031885
8                  0.031547
9                  0.031213
10                  0.030884
11                  0.030560
12                  0.030240
13                  0.029924
14                  0.029613
15                  0.029307
16                  0.029004
17                  0.028706
18                  0.028412
19                  0.028123
20                  0.027837
21                  0.027555
22                  0.027277
23                  0.027003
24                  0.026733
25                  0.026466
26                  0.026203
27                  0.025944
28                  0.025688
29                  0.025436
30                  0.025188
31                  0.024942
32                  0.024700
33                  0.024462
34                  0.024227
35                  0.023995
36                  0.023766
37                  0.023540
38                  0.023317
39                  0.023097
40                  0.022881
41                  0.022667
42                  0.022456
43                  0.022248
```

44	0.022043
45	0.021840
46	0.021641
47	0.021444
48	0.021249
49	0.021057
50	0.020868
51	0.020681
52	0.020497
53	0.020315
54	0.020136
55	0.019959
56	0.019784
57	0.019612
58	0.019442
59	0.019274
60	0.019108
61	0.018945
62	0.018783
63	0.018624
64	0.018467
65	0.018312
66	0.018159
67	0.018008
68	0.017859
69	0.017711
70	0.017566
71	0.017422
72	0.017281
73	0.017141
74	0.017003
75	0.016867
76	0.016732
77	0.016599
78	0.016468
79	0.016339
80	0.016211
81	0.016085
82	0.015960
83	0.015837
84	0.015715
85	0.015595
86	0.015477
87	0.015360
88	0.015244
89	0.015130
90	0.015017
91	0.014906

92	0.014796
93	0.014687
94	0.014580
95	0.014474
96	0.014369
97	0.014265
98	0.014163
99	0.014062
100	0.013962
101	0.013864
102	0.013767
103	0.013670
104	0.013575
105	0.013481
106	0.013389
107	0.013297
108	0.013206
109	0.013117
110	0.013028
111	0.012941
112	0.012855
113	0.012769
114	0.012685
115	0.012601
116	0.012519
117	0.012437
118	0.012357
119	0.012277
120	0.012199
121	0.012121
122	0.012044
123	0.011968
124	0.011893
125	0.011818
126	0.011745
127	0.011672
128	0.011600
129	0.011529
130	0.011459
131	0.011390
132	0.011321
133	0.011253
134	0.011186
135	0.011119
136	0.011054
137	0.010989
138	0.010925
139	0.010861

140	0.010798
141	0.010736
142	0.010674
143	0.010614
144	0.010553
145	0.010494
146	0.010435
147	0.010377
148	0.010319
149	0.010262
150	0.010205
151	0.010150
152	0.010094
153	0.010040
154	0.009985
155	0.009932
156	0.009879
157	0.009826
158	0.009774
159	0.009723
160	0.009672
161	0.009622
162	0.009572
163	0.009522
164	0.009474
165	0.009425
166	0.009377
167	0.009330
168	0.009283
169	0.009236
170	0.009190
171	0.009145
172	0.009100
173	0.009055
174	0.009011
175	0.008967
176	0.008923
177	0.008880
178	0.008838
179	0.008796
180	0.008754
181	0.008712
182	0.008671
183	0.008631
184	0.008591
185	0.008551
186	0.008511
187	0.008472

188	0.008433
189	0.008395
190	0.008357
191	0.008319
192	0.008281
193	0.008244
194	0.008208
195	0.008171
196	0.008135
197	0.008099
198	0.008064
199	0.008028
200	0.007994
201	0.007959
202	0.007925
203	0.007891
204	0.007857
205	0.007823
206	0.007790
207	0.007757
208	0.007725
209	0.007692
210	0.007660
211	0.007629
212	0.007597
213	0.007566
214	0.007535
215	0.007504
216	0.007473
217	0.007443
218	0.007413
219	0.007383
220	0.007353
221	0.007324
222	0.007295
223	0.007266
224	0.007237
225	0.007208
226	0.007180
227	0.007152
228	0.007124
229	0.007096
230	0.007069
231	0.007041
232	0.007014
233	0.006987
234	0.006961
235	0.006934

```
236                   0.006908
237                   0.006881
238                   0.006855
239                   0.006830
240                   0.006804
241                   0.006778
242                   0.006753
243                   0.006728
244                   0.006703
245                   0.006678
246                   0.006653
247                   0.006629
248                   0.006604
249                   0.006580
250                   0.006556
```

In [63]:
```
# Test for the best number of latent feature. (with latent features 5)
user_mat_5, offer_mat_5 = FunkSVD(np_train, latent_features=5, learning_rate=0.005, ite
```

```
Optimizaiton Statistics
Iterations | Mean Squared Error
1                   0.050672
2                   0.045327
3                   0.044160
4                   0.043192
5                   0.042267
6                   0.041368
7                   0.040492
8                   0.039640
9                   0.038810
10                   0.038002
11                   0.037216
12                   0.036450
13                   0.035705
14                   0.034979
15                   0.034272
16                   0.033584
17                   0.032915
18                   0.032262
19                   0.031627
20                   0.031009
21                   0.030407
22                   0.029821
23                   0.029250
24                   0.028694
25                   0.028153
26                   0.027625
```

27	0.027112
28	0.026612
29	0.026125
30	0.025650
31	0.025188
32	0.024737
33	0.024298
34	0.023871
35	0.023454
36	0.023048
37	0.022653
38	0.022267
39	0.021892
40	0.021525
41	0.021168
42	0.020820
43	0.020481
44	0.020150
45	0.019828
46	0.019514
47	0.019207
48	0.018908
49	0.018616
50	0.018332
51	0.018054
52	0.017784
53	0.017519
54	0.017262
55	0.017010
56	0.016765
57	0.016526
58	0.016292
59	0.016064
60	0.015841
61	0.015624
62	0.015412
63	0.015205
64	0.015003
65	0.014805
66	0.014612
67	0.014424
68	0.014240
69	0.014061
70	0.013885
71	0.013714
72	0.013546
73	0.013383
74	0.013223

75	0.013067
76	0.012914
77	0.012765
78	0.012619
79	0.012476
80	0.012337
81	0.012201
82	0.012068
83	0.011937
84	0.011810
85	0.011686
86	0.011564
87	0.011445
88	0.011328
89	0.011214
90	0.011103
91	0.010994
92	0.010887
93	0.010783
94	0.010681
95	0.010581
96	0.010483
97	0.010387
98	0.010294
99	0.010202
100	0.010112
101	0.010024
102	0.009938
103	0.009854
104	0.009772
105	0.009691
106	0.009612
107	0.009535
108	0.009459
109	0.009385
110	0.009312
111	0.009241
112	0.009171
113	0.009102
114	0.009035
115	0.008970
116	0.008905
117	0.008842
118	0.008781
119	0.008720
120	0.008661
121	0.008603
122	0.008546

123	0.008490
124	0.008435
125	0.008381
126	0.008329
127	0.008277
128	0.008226
129	0.008177
130	0.008128
131	0.008080
132	0.008033
133	0.007987
134	0.007942
135	0.007898
136	0.007855
137	0.007812
138	0.007770
139	0.007730
140	0.007689
141	0.007650
142	0.007611
143	0.007573
144	0.007536
145	0.007499
146	0.007463
147	0.007428
148	0.007393
149	0.007359
150	0.007326
151	0.007293
152	0.007260
153	0.007229
154	0.007198
155	0.007167
156	0.007137
157	0.007108
158	0.007079
159	0.007050
160	0.007022
161	0.006995
162	0.006967
163	0.006941
164	0.006915
165	0.006889
166	0.006864
167	0.006839
168	0.006814
169	0.006790
170	0.006767

171	0.006744
172	0.006721
173	0.006698
174	0.006676
175	0.006654
176	0.006633
177	0.006612
178	0.006591
179	0.006571
180	0.006550
181	0.006531
182	0.006511
183	0.006492
184	0.006473
185	0.006454
186	0.006436
187	0.006418
188	0.006400
189	0.006383
190	0.006365
191	0.006348
192	0.006331
193	0.006315
194	0.006298
195	0.006282
196	0.006266
197	0.006251
198	0.006235
199	0.006220
200	0.006205
201	0.006190
202	0.006176
203	0.006161
204	0.006147
205	0.006133
206	0.006119
207	0.006105
208	0.006092
209	0.006078
210	0.006065
211	0.006052
212	0.006039
213	0.006026
214	0.006014
215	0.006001
216	0.005989
217	0.005976
218	0.005964

```
219                     0.005952
220                     0.005941
221                     0.005929
222                     0.005917
223                     0.005906
224                     0.005895
225                     0.005883
226                     0.005872
227                     0.005861
228                     0.005850
229                     0.005839
230                     0.005829
231                     0.005818
232                     0.005808
233                     0.005797
234                     0.005787
235                     0.005777
236                     0.005766
237                     0.005756
238                     0.005746
239                     0.005736
240                     0.005727
241                     0.005717
242                     0.005707
243                     0.005697
244                     0.005688
245                     0.005678
246                     0.005669
247                     0.005660
248                     0.005650
249                     0.005641
250                     0.005632
```

Based on the MSE value the model with 5 latent featues seems to be performing the best. However, that could be a case of overfitting.Therefore we will validate our results by making predictions on the test dataset.

Check performance of the FUNKSVD models with the various number of latent features against the test dataset

```
In [77]: #Predict reaction function
         def predict_reaction(user_matrix, offer_matrix, user_id, offer_id):
             '''
             INPUT:
             user_matrix - user by latent factor matrix
             offer_matrix - latent factor by offer matrix
             user_id - the user_id from the reviews df
             offer_id - the offer_id according the offer df
```

```
        OUTPUT:
        pred - the predicted reaction for user_id-offer_id according to FunkSVD
        '''
        try:
            # Use the training data to create a series of users and movies that matches the
            user_ids_series = np.array(train_matrix.index)
            offer_ids_series = np.array(train_matrix.columns)

            # User row and offer Column
            user_row = np.where(user_ids_series == user_id)[0][0]
            offer_col = np.where(offer_ids_series == offer_id)[0][0]

            # Take dot product of that row and column in U and V to make prediction
            pred = np.dot(user_matrix[user_row, :], offer_matrix[:, offer_col])

            return pred

        except:
            return None
```

In [78]:
```
#Generate validation score function
def validation_score(test_matrix, user_mat, offer_mat):
    '''Measure the squared errors for the prediction'''
    num_complete = np.count_nonzero(~np.isnan(test_matrix))

    sse_accum = 0

    for user_id in test_matrix.index:
        for offer_id in test_matrix.columns:
            if ~np.isnan(test_matrix.loc[user_id, offer_id]):
                predict_value = predict_reaction(user_mat, offer_mat, user_id, offer_id
                if predict_value != None:
                    # compute the error as the actual minus the dot product of the user
                    diff = test_matrix.loc[user_id, offer_id] - predict_value #predict_

                    # Keep track of the sum of squared errors for the matrix
                    sse_accum += diff**2

    print('Validation score: ',sse_accum / num_complete)
```

In [79]:
```
# Evaluation for latent features of 20
validation_score(test_matrix, user_mat_20, offer_mat_20)
```

```
Validation score:  0.910342981753
```

In [80]:
```
# Evaluation for latent features of 15
validation_score(test_matrix, user_mat_15, offer_mat_15)
```

```
Validation score:  0.912873762423
```

```
In [81]: # Evaluation for latent features of 10
         validation_score(test_matrix, user_mat_10, offer_mat_10)
```

```
Validation score:  0.912808052255
```

```
In [82]: # Evaluation for latent features of 5
         validation_score(test_matrix, user_mat_5, offer_mat_5)
```

```
Validation score:  0.899251210168
```

Based on the validation scores the model using latent featues of 5 seems to be performing the best.

2.5 Make Recomendations

Since our training dataset only consists of some users, we need to have a recommendation engine that can also handle a new user. Below functions will help make default offer recommendations to a new Customer by recommending offer which generated the maximum reactions from existing Customers.

```
In [203]: def offer_max_reactions(user_item_matrix):
              # Find out which offer is accepted the most number of times

              offer_count = []
              for offer_id in user_item_matrix.columns:
                  offer_count.append([offer_id, len(transcript_df[(transcript_df['person'].isin(

              offer_reactions = pd.DataFrame(offer_count, columns=['offer_id', 'Total_reactions'
              offer_reactions['Total_reactions'] = pd.to_numeric(offer_reactions['Total_reaction
              offer_reactions.sort_values(by='Total_reactions', ascending=False, inplace=True)

              return offer_reactions
```

```
In [204]: offer_reactions=offer_max_reactions(all_df)
          offer_reactions=offer_reactions.merge(portfolio[['id','offer_type']], left_on='offer_i
```

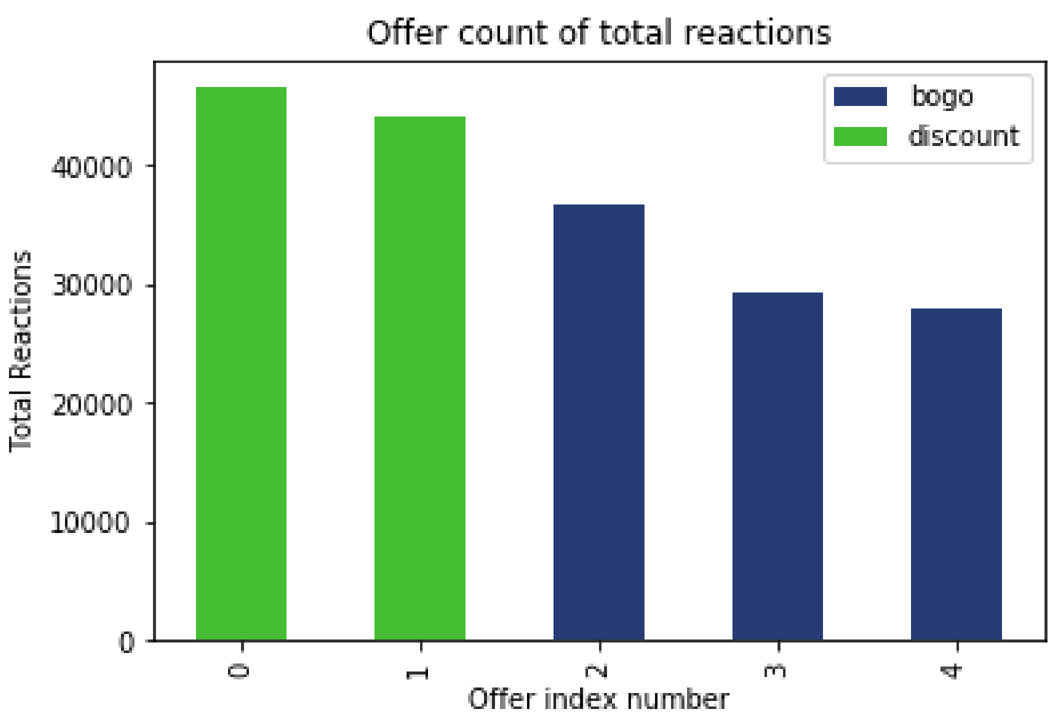
```
In [206]: offer_reactions
```

```
Out[206]:                            offer_id  Total_reactions  \
          0  fafdcd668e3743c1bb461111dcafc2a4            46510
          1  2298d6c36e964ae4a3e7e9706d1fb8c2            44077
          2  f19421c1d4aa40978ebb69ca19b0e20d            36627
          3  4d5c57ea9a6940dd891ad53e9dbe8da0            29375
          4  ae264e3637204a6fb9bb56bc8210ddfd            27855
```

```
                                 id offer_type
0  fafdcd668e3743c1bb461111dcafc2a4   discount
1  2298d6c36e964ae4a3e7e9706d1fb8c2   discount
2  f19421c1d4aa40978ebb69ca19b0e20d       bogo
3  4d5c57ea9a6940dd891ad53e9dbe8da0       bogo
4  ae264e3637204a6fb9bb56bc8210ddfd       bogo
```

In [215]:
```python
colours = {"bogo": "#273c75", "discount": "#44bd32"}
offer_reactions['Total_reactions'].plot(
        kind="bar", color=offer_reactions['offer_type'].replace(colours)
).legend(
    [
        Patch(facecolor=colours['bogo']),
        Patch(facecolor=colours['discount'])
    ], ["bogo", "discount"]
)
plt.title('Offer count of total reactions')
plt.xlabel('Offer index number')
plt.ylabel('Total Reactions')
```

Out[215]: Text(0,0.5,'Total Reactions')



From the above chart it is clear that discount is the best performing offer in the dataset
Develop final recomendation engine that uses model and default recomendations as well

```
In [176]: def make_recommendations(user_id, user_mat, offer_mat):
              reccomendations = {}
              for offer_id in train_matrix.columns:
                  pred_val = predict_reaction(user_mat, offer_mat, user_id, offer_id)
                  if pred_val != None:
                      reccomendations[offer_id] = pred_val
              if pred_val == None:
                  print("Since this user is new, we are reccomending the best performing offer")
                  print(offer_reactions.head(1))
              else:
                  import operator
                  from more_itertools import take
                  reccomendations= dict( sorted(reccomendations.items(), key=operator.itemgetter
                  top_reccomendation = take(1, reccomendations.items())
                  for offer_id, pred_val in top_reccomendation:
                      print("offer id: ", offer_id, " predicted value: ", round(pred_val,2))
```

```
In [177]: #Make best reccomendation for existing user
          make_recommendations('0610b486422d4921ae7d2bf64640c50b', user_mat_5, offer_mat_5)
```

```
offer id:  2906b810c7d4411798c6938adc9daaa5  predicted value:  1.41
```

```
In [178]: # Make best reccomendation for new user
          make_recommendations('new_user', user_mat_5, offer_mat_5)
```

```
Since this user is new, we are reccomending the best performing offer
                           offer_id  Total_reactions
7  fafdcd668e3743c1bb461111dcafc2a4            46510
```

2.6 6. Next steps and improvements

In order to improve the above recommendation engine, I would suggest the following approaches. * The default recommendation for new users can be improved by accounting for demographic information such as gender, age, etc assuming such information is available to us * Alternatively algorithms apart from Funk SVD or neural networks can be explored

2.7 7.Credits and references

- Starbucks and Udacity for dataset
- https://stackoverflow.com/questions
- Udacity implementing 'Matrix factorization for Recommendations' lesson for function implementations such as FunkSVD, User item matrix creations, prediction and validation

```
In [ ]:
```