Starbucks_Capstone_notebook

March 30, 2022

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.

```
In [1]: import pandas as pd
        import numpy as np
        import math
        import json
        import matplotlib.pyplot as plt
        %matplotlib inline

        import seaborn as sns
        from joblib import dump, load

        from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, Gradien
        from sklearn.neighbors import KNeighborsClassifier as KNN
        from sklearn.metrics import confusion_matrix, accuracy_score, classification_report,f1_s
        from sklearn import preprocessing

        from sklearn.model_selection import train_test_split, RandomizedSearchCV, GridSearchCV
        from sklearn.metrics import accuracy_score, f1_score, fbeta_score, make_scorer, mean_squ
        from sklearn.linear_model import LogisticRegression
```

```
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)
```

3 Data Cleaning

In order to have a good understanding of the data, let us take time to clean and explore the data to determine the best procedure to clean up the data. This would enable us check for missing value, visualizing the data distribution

```
In [3]: portfolio.head()
```

```
Out[3]:                        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 [27]: profile.head()
```

```
Out[27]:    age  became_member_on gender                                id    income  \
         0  118              1872   None  68be06ca386d4c31939f3a4f0e3dd783       NaN
         1   55              1719      F  0610b486422d4921ae7d2bf64640c50b  112000.0
         2  118              1357   None  38fe809add3b4fcf9315a9694bb96ff5       NaN
         3   75              1786      F  78afa995795e4d85b5d9ceeca43f5fef  100000.0
         4  118              1699   None  a03223e636434f42ac4c3df47e8bac43       NaN

            valid
         0      0
         1      1
         2      0
         3      1
         4      0
```

```
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 [6]: from collections import Counter
        def clean_portfolio(df):
            '''
            Description:
                Deserialize the channels attribute to create column header for each of them alon
                Merge the portfolio dataframe with the stacked data using the id field
                Drop the channels column from the dataset
                Rename the id field as offer_id
                Convert the duration data to hours instead of days
                drop any duplicates if any
            Input:
                - df: original portfolio dataframe
            Returns:
                - portfolio_df - the cleaned portfolio dataframe
            '''
            #deserialize the channels attribute to form each item to a column and their respecti
            #Convert categorical variable into dummy/indicator variables.
            #credit to https://stackoverflow.com/questions/70139966/how-to-transform-dataframe-c
            portfolio_stacked = df.set_index('id')['channels'].map(Counter).apply(pd.Series).fil
            #merge the stacked df and the main df to form the collective data
            portfolio_df = df.merge(portfolio_stacked,how='left',on='id')
            #drop the original channels data
            portfolio_df.drop(columns='channels', inplace=True)

            #:portfolio represent Offers sent during 30-day test period (10 offers x 6 fields)
            #we can rename the portfolio id as the offer_id
            portfolio_df.rename(columns={'id':'offer_id'}, inplace=True)

            #convert the offertypes to columns
            offer_types = pd.get_dummies(portfolio_df['offer_type'].str.lower(), prefix="offer")
            portfolio_df = pd.concat([portfolio_df,offer_types],axis=1)
            portfolio_df.drop(columns='offer_type', inplace=True)

            #drop duplicated if any
            portfolio_df.drop_duplicates(inplace=True)

            return portfolio_df

        portfolio_df = clean_portfolio(portfolio)
```

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

```
Out[7]:    difficulty  duration                          offer_id  reward  email  \
        0          10         7  ae264e3637204a6fb9bb56bc8210ddfd      10      1
        1          10         5  4d5c57ea9a6940dd891ad53e9dbe8da0      10      1
        2           0         4  3f207df678b143eea3cee63160fa8bed       0      1
        3           5         7  9b98b8c7a33c4b65b9aebfe6a799e6d9       5      1
        4          20        10  0b1e1539f2cc45b7b9fa7c272da2e1d7       5      1

           mobile  social  web  offer_bogo  offer_discount  offer_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
```

```
In [8]: import datetime
        def clean_profile(df):
            '''
            Description: Clean the profile data frame.
                - Format the date field to a standard date format
                - Create a columns name for all confirmed users using afte inpecting the dataset
                - Extract dummy or indicator variable from the categorical attribute gender
                - Merge the dummy data with the main dataset
                - Drop any duplicates if need be
            Input:
```

```
            - df: original profile dataframe
        Returns:
            - profile_df - the cleaned profile dataframe
        '''
        df['became_member_on'] = pd.to_datetime(df['became_member_on'], format='%Y%m%d')
        df['valid'] = (df.age != 118).astype(int)

        # Convert categorical variable line gender into dummy/indicator variables.
        #https://pandas.pydata.org/docs/reference/api/pandas.get_dummies.html
        dummies = pd.get_dummies(df['gender'].str.lower(), prefix="gender").groupby(df['id']
        #dummies_years = pd.get_dummies(df['became_member_on'].apply(lambda x: x.year)).grou
        df['became_member_on']  = df['became_member_on'].apply(lambda x: int((pd.to_datetime

        #merge the stacked df and the main df to form the collective data
        profile_df = df.merge(dummies,how='left',on='id')
        #profile_df = df.merge(dummies_years,how='left',on='id')

        #we can rename the profile id as the user_id
        profile_df.rename(columns={'id':'customer_id'}, inplace=True)


        #drop duplicated if any
        profile_df.drop_duplicates(inplace=True)
        #profile_df.dropna(inplace=True)

        return profile_df

    #Test the clean_profile function
    profile_df = clean_profile(profile)
    profile_df.head()
```

```
Out[8]:    age  became_member_on gender                       customer_id    income  \
        0  118              1872   None  68be06ca386d4c31939f3a4f0e3dd783       NaN
        1   55              1719      F  0610b486422d4921ae7d2bf64640c50b  112000.0
        2  118              1357   None  38fe809add3b4fcf9315a9694bb96ff5       NaN
        3   75              1786      F  78afa995795e4d85b5d9ceeca43f5fef  100000.0
        4  118              1699   None  a03223e636434f42ac4c3df47e8bac43       NaN

           valid  gender_f  gender_m  gender_o
        0      0         0         0         0
        1      1         1         0         0
        2      0         0         0         0
        3      1         1         0         0
        4      0         0         0         0
```

```
In [9]: transcript.head(5)
```

```
Out[9]:             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 [10]: def clean_transcript(df):
             '''
             Dataset contains the following attributes
             - person: (string/hash)
             - event: (string) offer received, offer viewed, transaction, offer completed
             - value: (dictionary) different values depending on event type (offers and transact
             offer id: (string/hash) not associated with any "transaction"
             amount: (numeric) money spent in "transaction
             reward: (numeric) money gained from "offer completed"
             (numeric) hours after start of test
             Description: Clean the profile data frame.
                 - replace every space with underscore (_) to get a valid column name
                 - Extract dummy or indicator variable from the categorical attribute event
                 - Merge the dummy data with the main dataset

             Input:
                 - df: original transcript dataframe
             Returns:
                 - transcript_df - the cleaned transcript dataframe
             '''
             # Split event into several dummy columns
             #create expected fields
             transcript_df = df.copy()
             #introdue an underscore as a word separator for the events
             transcript_df.event = transcript_df.event.str.replace(' ', '_')

             #create offer_if, amount and reward fields from the value collections
             transcript_df['offer_id'] = df['value'].apply(lambda x: x['offer_id'] if 'offer_id'
             transcript_df['amount'] = df['value'].apply(lambda x: x['amount'] if 'amount' in x
             transcript_df['reward'] = df['value'].apply(lambda x: x['reward'] if 'reward' in x

             #Drop the value field
             transcript_df.drop('value',axis=1,inplace=True)
             transcript_df.rename(columns={'person':'customer_id'},inplace=True)

             #Convert transcript time from hours to days
```

```
            transcript_df['time'] = df['time'] / 24

            #transform the event attribute to create columns for each customer for the offers
            transcript_df = transcript_df.groupby(['customer_id','offer_id','event'])['time'].c
            transcript_df.reset_index(level=[0,1],inplace = True)

            #Replace nan values with 0.0
            transcript_df.fillna(0.0, inplace = True)

            return transcript_df

        transcript_df = clean_transcript(transcript)
```

```
In [11]: transcript_df.head()
```

```
Out[11]: event                        customer_id                          offer_id  \
         0      0009655768c64bdeb2e877511632db8f  2906b810c7d4411798c6938adc9daaa5
         1      0009655768c64bdeb2e877511632db8f  3f207df678b143eea3cee63160fa8bed
         2      0009655768c64bdeb2e877511632db8f  5a8bc65990b245e5a138643cd4eb9837
         3      0009655768c64bdeb2e877511632db8f  f19421c1d4aa40978ebb69ca19b0e20d
         4      0009655768c64bdeb2e877511632db8f  fafdcd668e3743c1bb461111dcafc2a4

         event  offer_completed  offer_received  offer_viewed
         0                  1.0             1.0           0.0
         1                  0.0             1.0           1.0
         2                  0.0             1.0           1.0
         3                  1.0             1.0           1.0
         4                  1.0             1.0           1.0
```

```
In [12]: def combine_data(portfolio_df, profile_df, transcript_df):
             """ Combine transaction - transcript_df, demographic - profile_df and offer data -
             Input:
             - transcript_df
             - profile_df
             - portfolio_df
             Output:
             - merged_df: merged dataframe
             """
             #First merge the field that have a common join field (transcript_df and portfolio_d
             member_transactions = pd.merge(transcript_df, portfolio_df, how='left', on='offer_i

             #Merge the third dataframe with the common dataset
             merged_df = pd.merge(member_transactions, profile_df, how='left', on='customer_id')

             #Codify the offer_ids
             offer_idx = list(set(merged_df['offer_id']))

             for i in range(len(offer_idx)):
```

```
            merged_df['offer_id'] = merged_df['offer_id'].apply(lambda x: '{}'.format(i+1)

        #consider an offer to be successful if a viewed offer is completed
        merged_df.insert(loc=2, column='offer_successful', value=merged_df['offer_completed
        merged_df['offer_successful'] = merged_df['offer_successful'].apply(lambda x: 1.0 i
        merged_df.drop(columns=['offer_completed', 'offer_received', 'offer_viewed'], inpla

        return merged_df

    merged_df = combine_data(portfolio_df, profile_df, transcript_df)
```

```
In [13]: merged_df.shape
```

```
Out[13]: (63288, 21)
```

4 Descriptive Analysis and Data Exploration

4.0.1 Descriptive Analysis

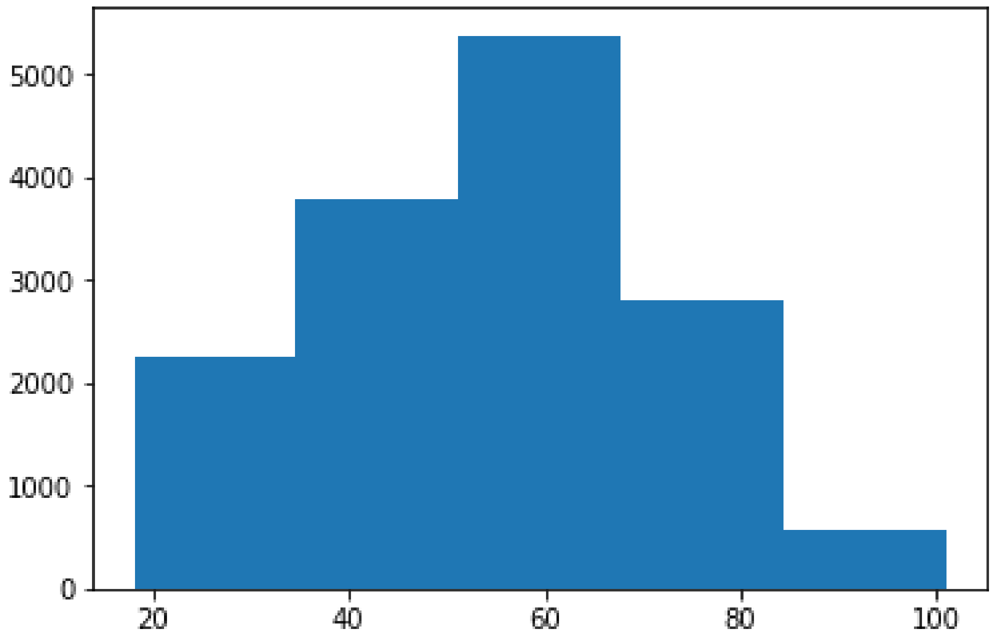
4.0.2 Lets use graphs, charts and decriptive statistics to get more insight from each data groups

```
In [33]: profile_df_copy = profile_df.copy()
         profile_df_copy = profile_df_copy[profile_df_copy['age'] != 118]
         profile_df_copy = profile_df_copy[profile_df_copy['income'].isnull() == False]
         profile_df_copy.describe()
```

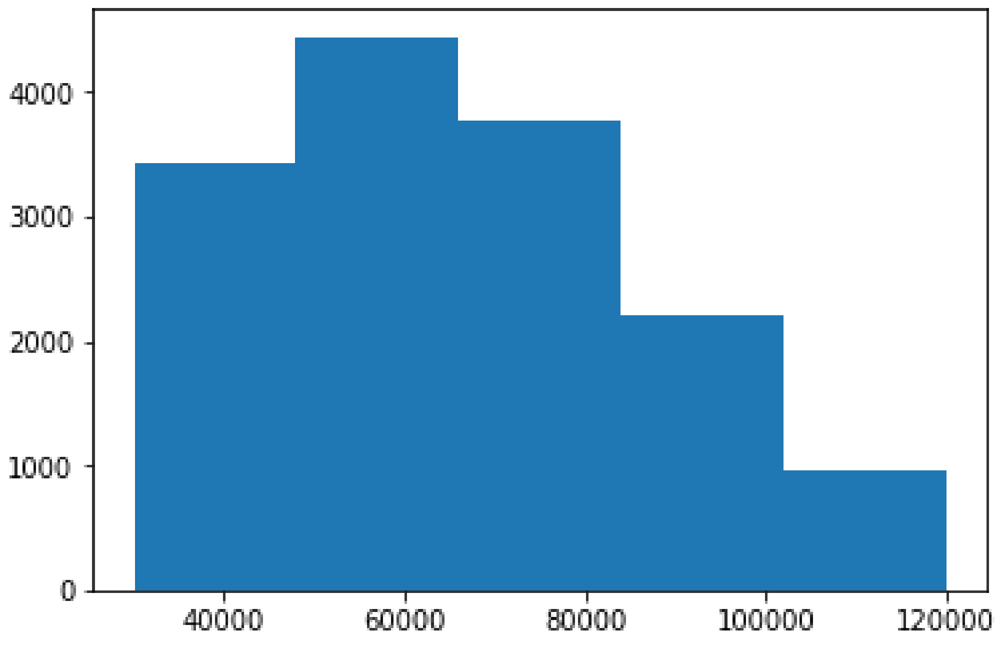
```
Out[33]:                 age  became_member_on         income    valid      gender_f  \
         count  14825.000000      14825.000000   14825.000000  14825.0  14825.000000
         mean      54.393524       1865.478988   65404.991568      1.0      0.413423
         std       17.383705        419.205158   21598.299410      0.0      0.492464
         min       18.000000       1343.000000   30000.000000      1.0      0.000000
         25%       42.000000       1551.000000   49000.000000      1.0      0.000000
         50%       55.000000       1701.000000   64000.000000      1.0      0.000000
         75%       66.000000       2140.000000   80000.000000      1.0      1.000000
         max      101.000000       3166.000000  120000.000000      1.0      1.000000

             gender_m      gender_o
         count  14825.000000  14825.000000
         mean       0.572277      0.014300
         std        0.494765      0.118729
         min        0.000000      0.000000
         25%        0.000000      0.000000
         50%        1.000000      0.000000
         75%        1.000000      0.000000
         max        1.000000      1.000000
```

From the above descriptive statistics, the average incomev (revenue generated through the offer) is about USD65,404.99 from a total of 14,825 participants/customers

```
In [20]: plt.hist(profile_df_copy['age'], bins=5);
```



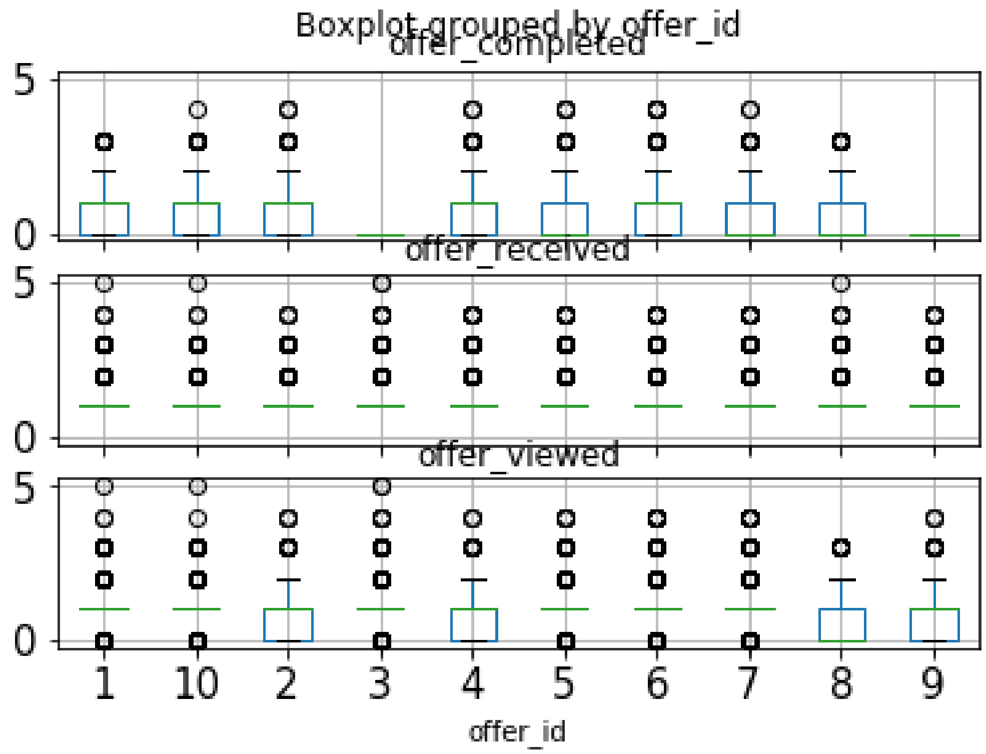
```
In [22]: valid_income = profile_df_copy[profile_df_copy['income'].isna()==False]

In [23]: plt.hist(valid_income['income'], bins=5)

Out[23]: (array([ 3438.,  4444.,  3780.,  2205.,   958.]),
          array([  30000.,   48000.,   66000.,   84000.,  102000.,  120000.]),
          <a list of 5 Patch objects>)
```



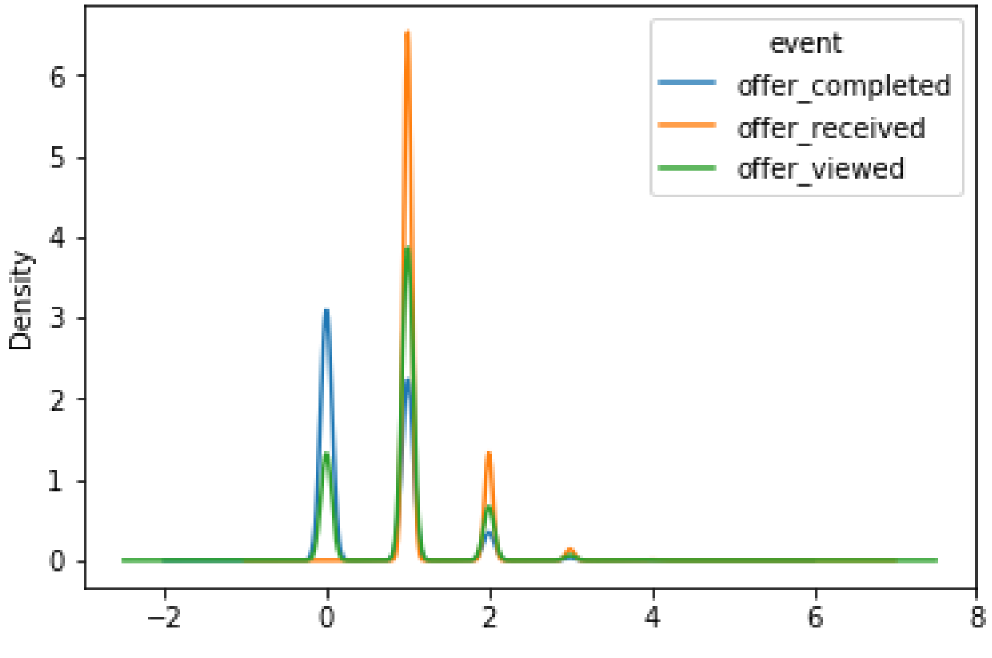
```
In [24]: transcript_df.describe()

Out[24]: event  offer_completed  offer_received  offer_viewed
         count     63288.000000    63288.000000   63288.00000
         mean          0.530575        1.205236       0.91210
         std           0.637582        0.453699       0.61458
         min           0.000000        1.000000       0.00000
         25%           0.000000        1.000000       1.00000
         50%           0.000000        1.000000       1.00000
         75%           1.000000        1.000000       1.00000
         max           4.000000        5.000000       5.00000
```

4.0.3 From the transaction descriptive statistics above, from the mean (offer completed = 0.53 and offer viewed = 0.91, about 39% difference), some of the customers that viewed the received offers were not able to complete the purchase whereas 67% of the offers received were not completed.

```
In [25]: transcript_df_copy = transcript_df.copy()
         offer_idx = list(set(transcript_df_copy.offer_id))
         for i in range(len(offer_idx)):
             transcript_df_copy['offer_id'] = transcript_df_copy['offer_id'].apply(lambda x: '{}

         boxplot = transcript_df_copy.boxplot(column=['offer_completed', 'offer_received', 'offe
```



```
In [26]: axes = transcript_df_copy.plot.kde()
```



From the above visual, although all the participants received the information to participate in the offers, only about to 38% of the population completed their offers.

4.0.4 The merged data show the summary of the three datasets and also reveals the number of records available

```
In [39]: merged_df.head(10)
```

```
Out[39]:                          customer_id offer_id  offer_successful  difficulty  \
         0  0009655768c64bdeb2e877511632db8f        4               0.0          10
         1  0009655768c64bdeb2e877511632db8f        9               0.0           0
         2  0009655768c64bdeb2e877511632db8f        3               0.0           0
         3  0009655768c64bdeb2e877511632db8f        1               1.0           5
         4  0009655768c64bdeb2e877511632db8f       10               1.0          10
         5  00116118485d4dfda04fdbaba9a87b5c        1               0.0           5
         6  0011e0d4e6b944f998e987f904e8c1e5        8               1.0          20
         7  0011e0d4e6b944f998e987f904e8c1e5        6               1.0           7
         8  0011e0d4e6b944f998e987f904e8c1e5        9               0.0           0
         9  0011e0d4e6b944f998e987f904e8c1e5        3               0.0           0

            duration  reward  email  mobile  social  web    ...     offer_discount  \
         0         7       2      1       1       0    1    ...                  1
         1         4       0      1       1       0    1    ...                  0
         2         3       0      1       1       1    0    ...                  0
         3         5       5      1       1       1    1    ...                  0
         4        10       2      1       1       1    1    ...                  1
         5         5       5      1       1       1    1    ...                  0
         6        10       5      1       0       0    1    ...                  1
         7         7       3      1       1       1    1    ...                  1
         8         4       0      1       1       0    1    ...                  0
         9         3       0      1       1       1    0    ...                  0

            offer_informational  age  became_member_on  gender   income  valid  \
         0                    0   33              1804       M  72000.0      1
         1                    1   33              1804       M  72000.0      1
         2                    1   33              1804       M  72000.0      1
         3                    0   33              1804       M  72000.0      1
         4                    0   33              1804       M  72000.0      1
         5                    0  118              1435    None      NaN      0
         6                    0   40              1541       O  57000.0      1
         7                    0   40              1541       O  57000.0      1
         8                    1   40              1541       O  57000.0      1
         9                    1   40              1541       O  57000.0      1

            gender_f  gender_m  gender_o
         0         0         1         0
         1         0         1         0
         2         0         1         0
```

```
3          0          1          0
4          0          1          0
5          0          0          0
6          0          0          1
7          0          0          1
8          0          0          1
9          0          0          1

[10 rows x 21 columns]
```

In [29]:
```
merged_df.describe()
```

Out[29]:
```
       offer_successful    difficulty      duration        reward    email  \
count      63288.000000  63288.000000  63288.000000  63288.000000  63288.0
mean           0.386487      7.711572      6.504819      4.206232      1.0
std            0.486948      5.541480      2.203565      3.402914      0.0
min            0.000000      0.000000      3.000000      0.000000      1.0
25%            0.000000      5.000000      5.000000      2.000000      1.0
50%            0.000000     10.000000      7.000000      5.000000      1.0
75%            1.000000     10.000000      7.000000      5.000000      1.0
max            1.000000     20.000000     10.000000     10.000000      1.0

             mobile        social           web    offer_bogo  offer_discount  \
count  63288.000000  63288.000000  63288.000000  63288.000000    63288.000000
mean       0.899286      0.599529      0.799425      0.400092        0.400013
std        0.300952      0.489998      0.400434      0.489921        0.489904
min        0.000000      0.000000      0.000000      0.000000        0.000000
25%        1.000000      0.000000      1.000000      0.000000        0.000000
50%        1.000000      1.000000      1.000000      0.000000        0.000000
75%        1.000000      1.000000      1.000000      1.000000        1.000000
max        1.000000      1.000000      1.000000      1.000000        1.000000

       offer_informational           age  became_member_on         income  \
count         63288.000000  63288.000000      63288.000000   55222.000000
mean              0.199896     62.462110       1859.721053   65388.595125
std               0.399925     26.729957        411.659882   21626.373809
min               0.000000     18.000000       1343.000000   30000.000000
25%               0.000000     45.000000       1551.000000   49000.000000
50%               0.000000     58.000000       1701.000000   63000.000000
75%               0.000000     73.000000       2134.000000   80000.000000
max               1.000000    118.000000       3166.000000  120000.000000

              valid      gender_f      gender_m      gender_o
count  63288.000000  63288.000000  63288.000000  63288.000000
mean       0.872551      0.360384      0.500016      0.012151
std        0.333478      0.480116      0.500004      0.109560
min        0.000000      0.000000      0.000000      0.000000
25%        1.000000      0.000000      0.000000      0.000000
```

```
50%         1.000000      0.000000      1.000000      0.000000
75%         1.000000      1.000000      1.000000      0.000000
max         1.000000      1.000000      1.000000      1.000000
```

5 Determine which demographic groups respond best to which offer type

```
In [30]: merged_df[merged_df['offer_successful'] == 1].offer_id.value_counts()
```

```
Out[30]: 10    4433
         6     4313
         1     3655
         5     2843
         7     2825
         2     2504
         4     2415
         8     1472
         Name: offer_id, dtype: int64
```

Provide descriptive statistics for all cases where customer's income was not reflected

```
In [17]: merged_df[merged_df['income'].isnull()][['age', 'income']].describe()
```

```
Out[17]:           age  income
         count  8066.0     0.0
         mean    118.0     NaN
         std       0.0     NaN
         min     118.0     NaN
         25%     118.0     NaN
         50%     118.0     NaN
         75%     118.0     NaN
         max     118.0     NaN
```

Provide descriptive statistics for all cases where customers' income exist

```
In [31]: merged_df[merged_df['income'].notnull()][['age', 'income']].describe()
```

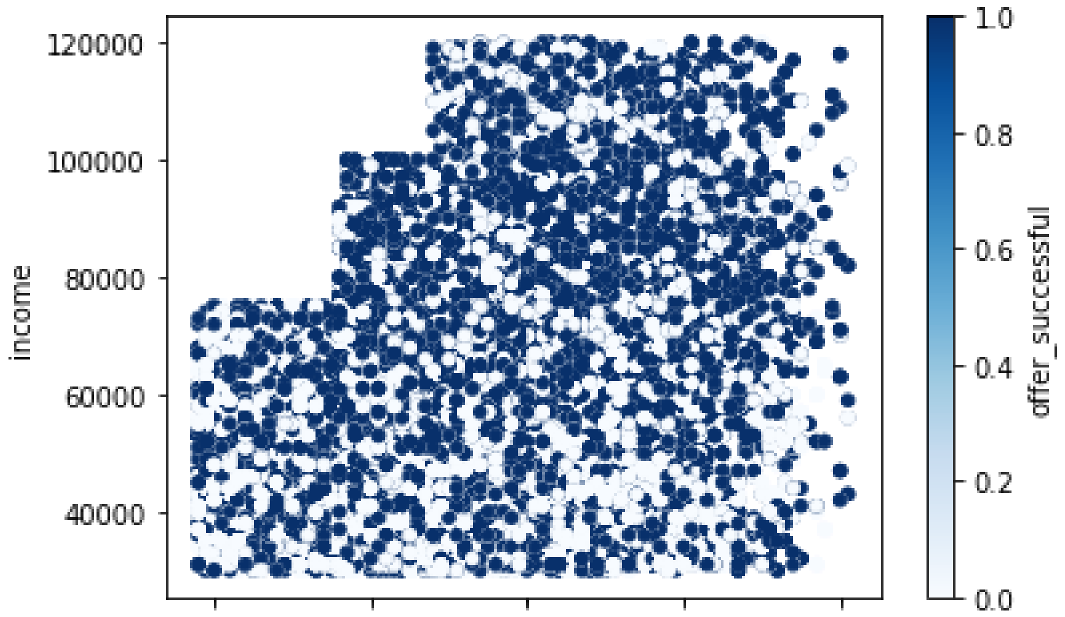
```
Out[31]:                 age          income
         count  55222.000000   55222.000000
         mean      54.349969   65388.595125
         std       17.392733   21626.373809
         min       18.000000   30000.000000
         25%       42.000000   49000.000000
         50%       55.000000   63000.000000
         75%       66.000000   80000.000000
         max      101.000000  120000.000000
```

Evaluate year membership record by year using the field became_member_on

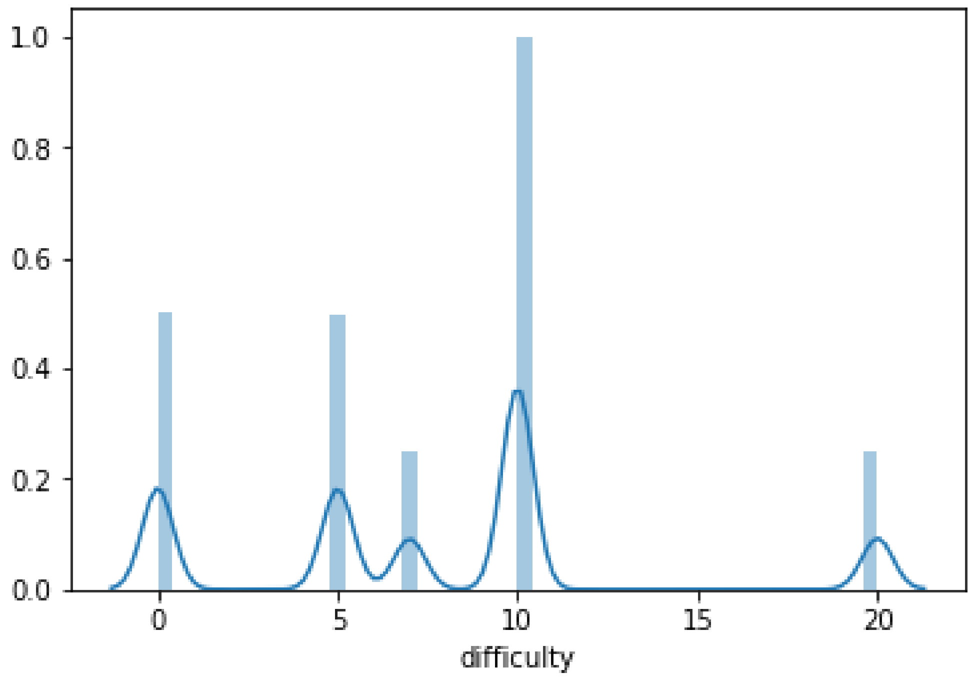
```
In [35]: #start_year = merged_df['became_member_on'].apply(lambda x: x.year).value_counts()
         #start_year
```

5.0.1 Data Visualization (contd)

```
In [36]: merged_df.plot.scatter(x='age', y='income', c='offer_successful', cmap='Blues')

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x7efcd17d8128>
```

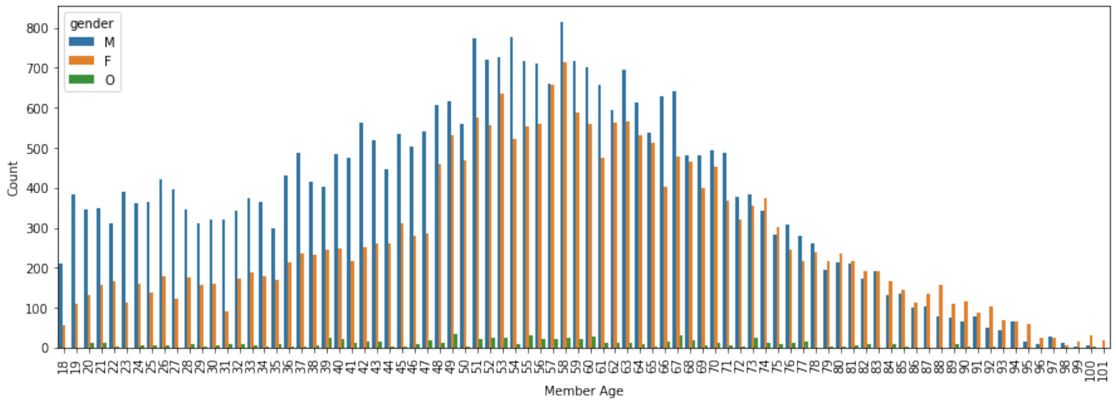


```
In [37]: sns.distplot(merged_df['difficulty'].dropna())

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7efcd18982b0>
```



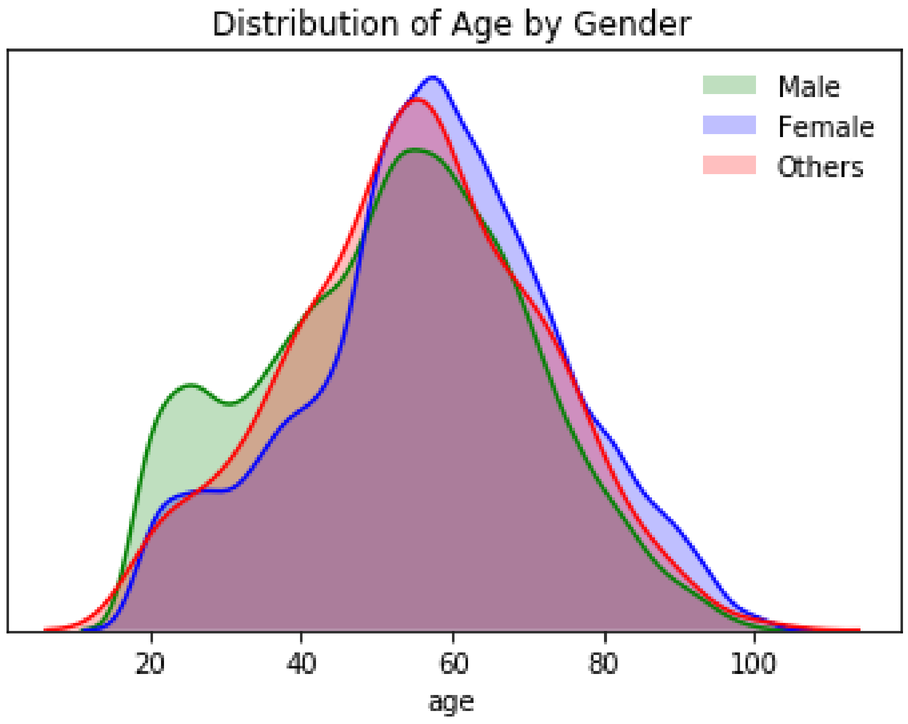
```
In [38]: #get the summary of ages of the participants
         age_df = merged_df.groupby(['gender', 'age']).size().sort_values(ascending=False) .rese
         plt.figure(figsize=(15, 5))
         sns.barplot(x='age', y='count', hue='gender', data=age_df)
         plt.xlabel('Member Age')
         plt.ylabel('Count')
         plt.xticks(rotation=90)
```

```
Out[38]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
                 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
                 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50,
                 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67,
                 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83]),
          <a list of 84 Text xticklabel objects>)
```



5.0.2 Plot distrribution of age by gender to see the response of each gender to offers accross ages

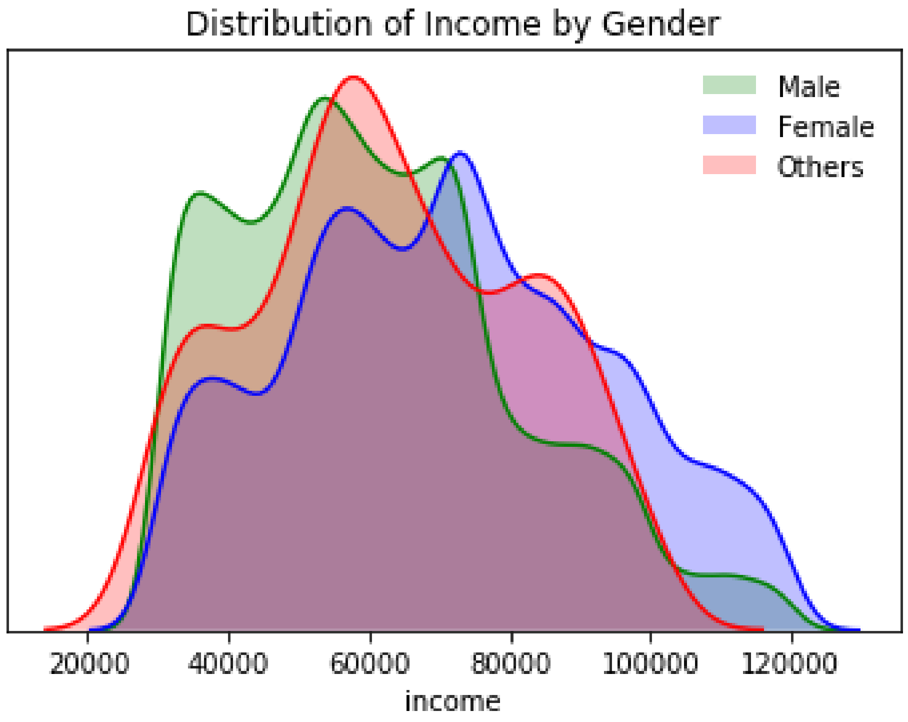
```
In [21]: sns.distplot(merged_df[merged_df['gender']=='M']['age'],hist=False,color="g", kde_kws={
         sns.distplot(merged_df[merged_df['gender']=='F']['age'],hist=False,color="b", kde_kws={
         sns.distplot(merged_df[merged_df['gender']=='O']['age'],hist=False,color="r", kde_kws={
         plt.title('Distribution of Age by Gender')
         plt.gca().get_yaxis().set_visible(False)
         plt.legend(['Male','Female', 'Others'],frameon=False);
```



From the diagram above, maximum patronage occured at age between 40-70 accross all gender

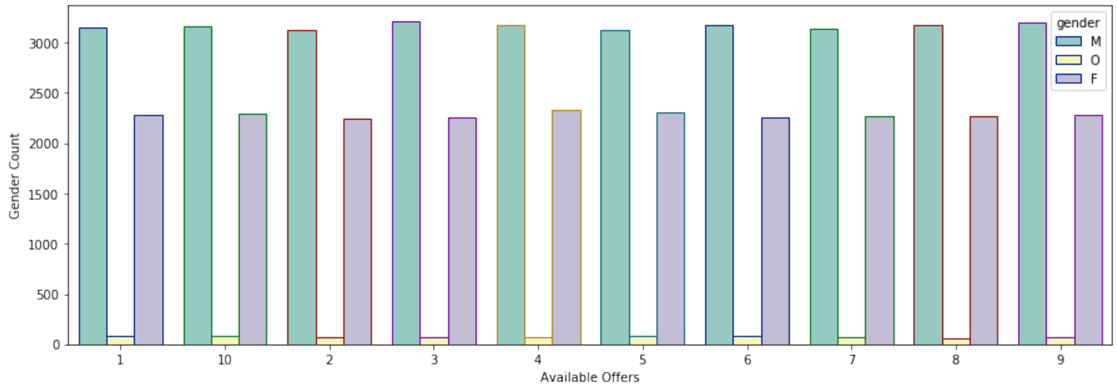
Plot distrribution of income by gender to see the response of each gender to offers based on income

```
In [22]: sns.distplot(merged_df[merged_df['gender']=='M']['income'],hist=False,color="g", kde_kw
         sns.distplot(merged_df[merged_df['gender']=='F']['income'],hist=False,color="b", kde_kw
         sns.distplot(merged_df[merged_df['gender']=='O']['income'],hist=False,color="r", kde_kw
         plt.title('Distribution of Income by Gender')
         plt.gca().get_yaxis().set_visible(False)
         plt.legend(['Male','Female', 'Others'],frameon=False);
```



5.0.3 Count of offers on Gender basis

```
In [23]: #gender_df = merged_df[merged_df['gender']=='M' or merged_df['gender']=='F']
         plt.figure(figsize=(15, 5))
         ax = sns.countplot(x="offer_id", hue="gender", data=merged_df, palette="Set3", edgecolo
         plt.xlabel('Available Offers')
         plt.ylabel('Gender Count')

Out[23]: Text(0,0.5,'Gender Count')
```

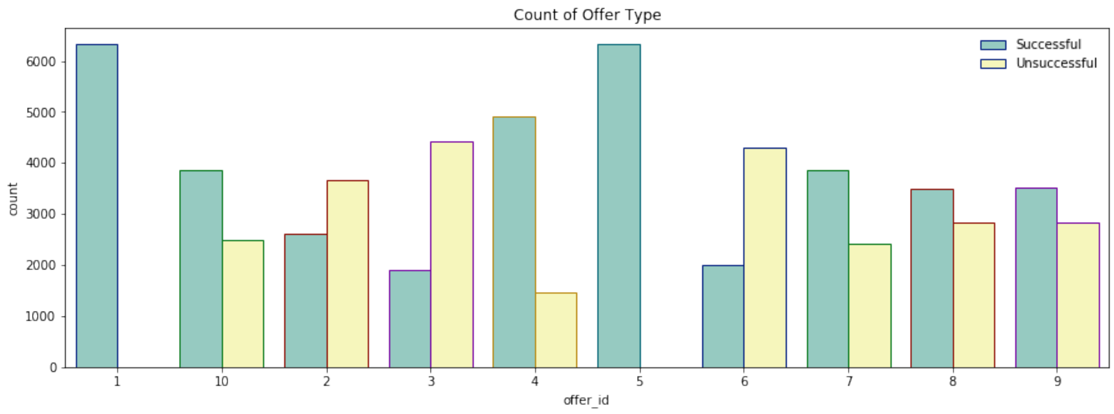


5.0.4 Analysis of successful and unsuccessful offers based on status, income, duration, difficulty and reward

1 Based on Status

```
In [24]: plt.figure(figsize=(15, 5))
         sns.countplot(x='offer_id',hue='offer_successful',data=merged_df, palette="Set3", edgec
         plt.legend(['Successful', 'Unsuccessful'],frameon=False)
         plt.title('Count of Offer Type')
```

```
Out[24]: Text(0.5,1,'Count of Offer Type')
```

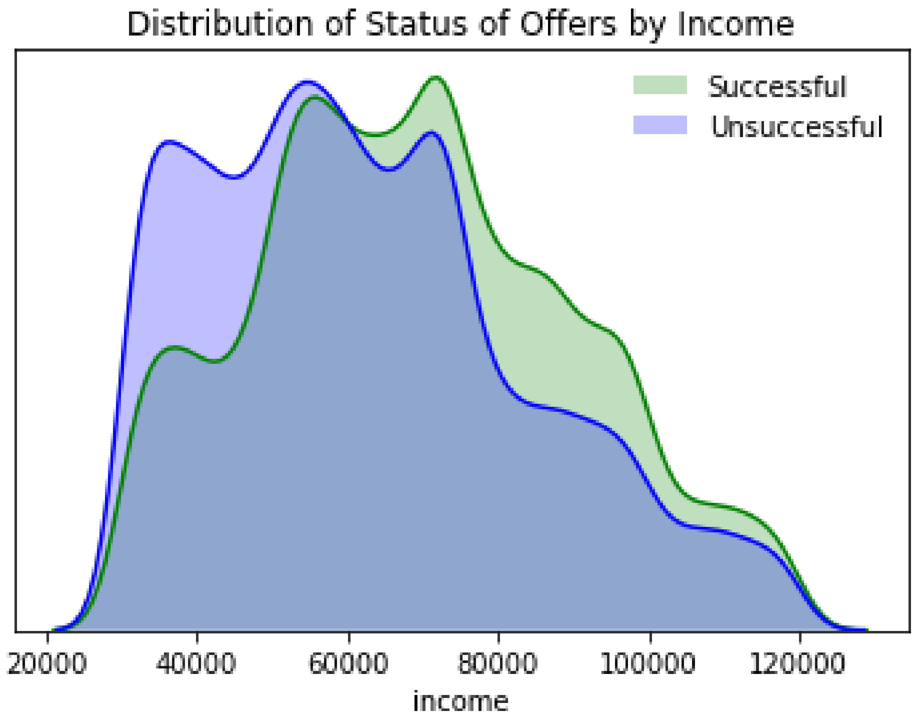


2. Based on Income

```
In [25]: sns.distplot(merged_df[merged_df['offer_successful'] == 1]['income'],hist=False,color="
         sns.distplot(merged_df[merged_df['offer_successful'] == 0]['income'],hist=False,color="
         plt.legend(['Successful', 'Unsuccessful'],frameon=False)
         plt.gca().get_yaxis().set_visible(False)
         plt.title('Distribution of Status of Offers by Income')
```

```
/opt/conda/lib/python3.6/site-packages/statsmodels/nonparametric/kde.py:454: RuntimeWarning: inv
  X = X[np.logical_and(X>clip[0], X<clip[1])] # won't work for two columns.
/opt/conda/lib/python3.6/site-packages/statsmodels/nonparametric/kde.py:454: RuntimeWarning: inv
  X = X[np.logical_and(X>clip[0], X<clip[1])] # won't work for two columns.
```

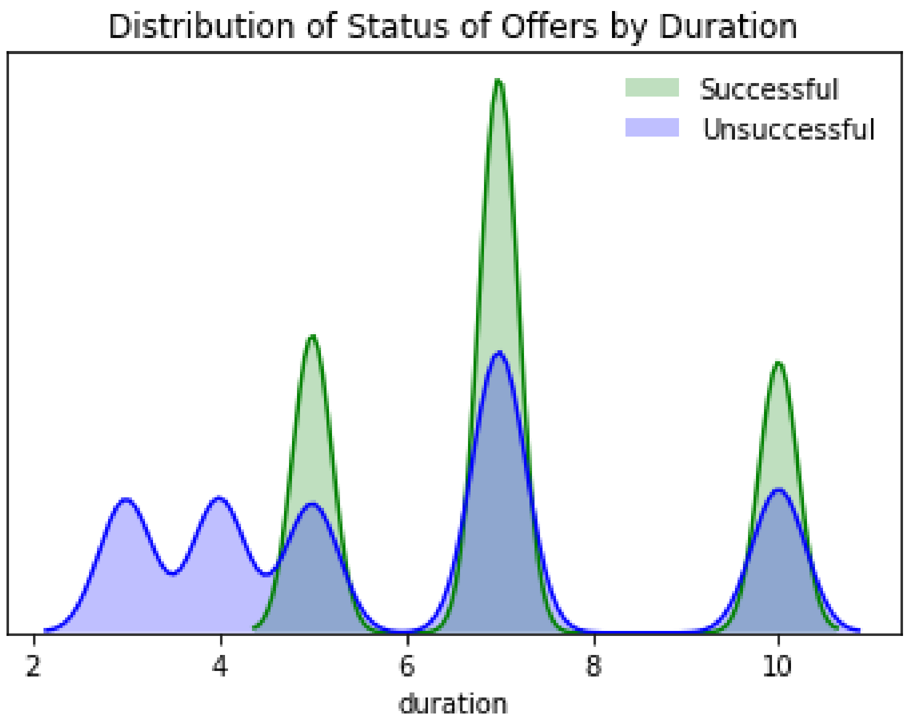
```
Out[25]: Text(0.5,1,'Distribution of Status of Offers by Income')
```



3. Based on Duration

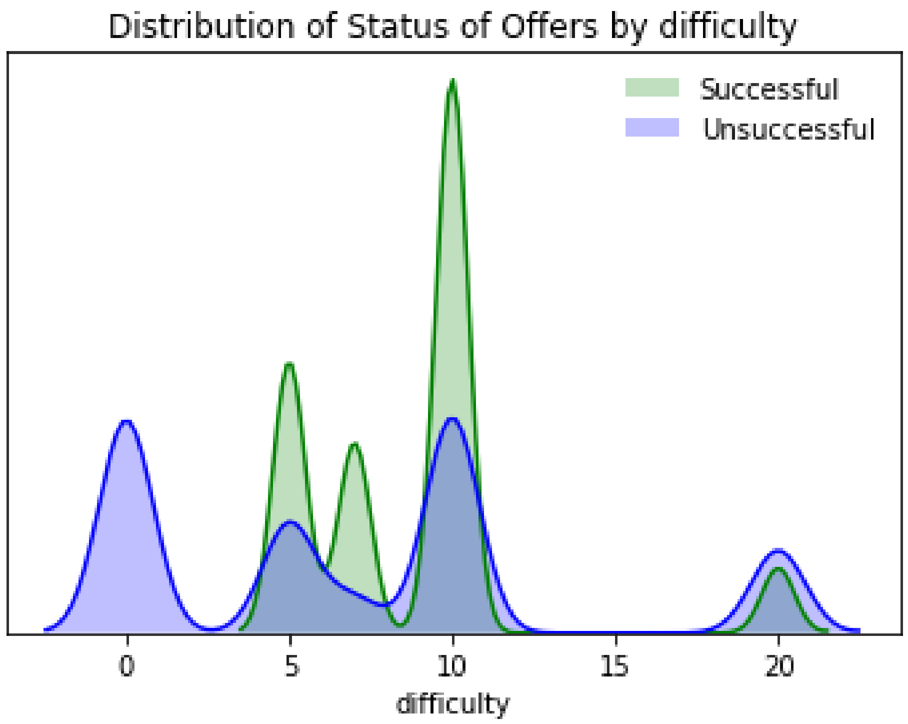
```
In [26]: sns.distplot(merged_df[merged_df['offer_successful'] > 0]['duration'],hist=False,color=
         sns.distplot(merged_df[merged_df['offer_successful']<= 0]['duration'],hist=False,color=
         plt.legend(['Successful', 'Unsuccessful'],frameon=False)
         plt.gca().get_yaxis().set_visible(False)
         plt.title('Distribution of Status of Offers by Duration')
```

```
Out[26]: Text(0.5,1,'Distribution of Status of Offers by Duration')
```



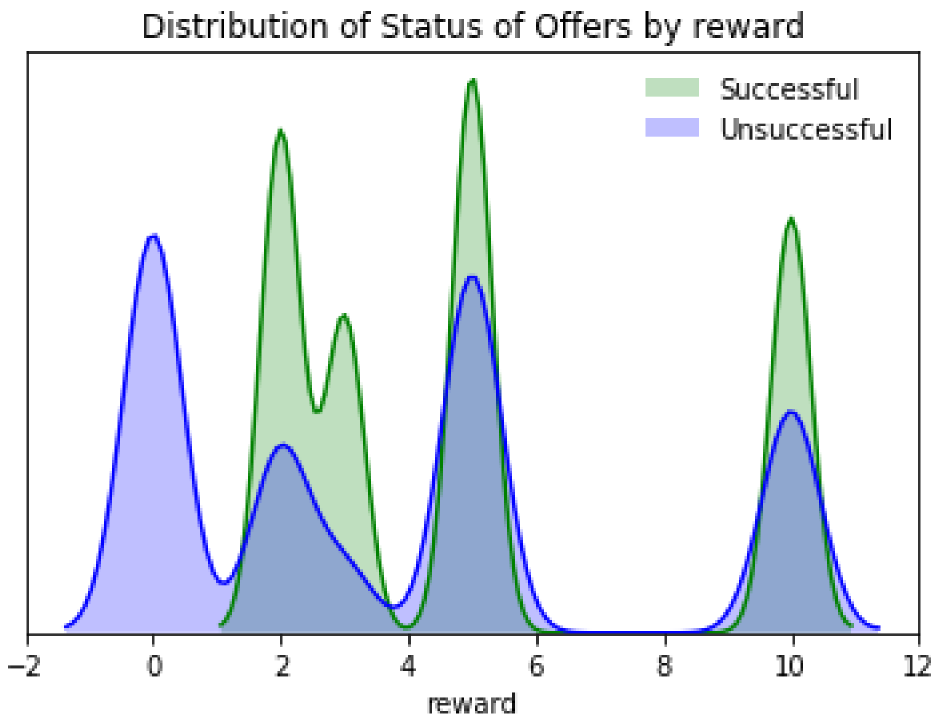
4. Based on difficulty

```
In [27]: sns.distplot(merged_df[merged_df['offer_successful']> 0]['difficulty'],hist=False,color
         sns.distplot(merged_df[merged_df['offer_successful']<= 0]['difficulty'],hist=False,colo
         plt.legend(['Successful', 'Unsuccessful'],frameon=False)
         plt.gca().get_yaxis().set_visible(False)
         plt.title('Distribution of Status of Offers by difficulty')

Out[27]: Text(0.5,1,'Distribution of Status of Offers by difficulty')
```



5. Based on reward

```
In [28]: sns.distplot(merged_df[merged_df['offer_successful'] > 0]['reward'],hist=False,color="g
         sns.distplot(merged_df[merged_df['offer_successful'] <= 0]['reward'],hist=False,color="
         plt.legend(['Successful', 'Unsuccessful'],frameon=False)
         plt.gca().get_yaxis().set_visible(False)
         plt.title('Distribution of Status of Offers by reward')

Out[28]: Text(0.5,1,'Distribution of Status of Offers by reward')
```



5.0.5 Modeling

Let us explore the some modelling techniques to perform some exploratory analysis. Modeling techniques are used in data evaluation and analysis. We would reveal some important findings the best performing offers, etc using these modelling techniques.

```
In [40]: merged_df.loc[merged_df['offer_successful'] == 1].head()
```

```
Out[40]:                         customer_id offer_id  offer_successful  difficulty  \
         3   0009655768c64bdeb2e877511632db8f        1               1.0           5
         4   0009655768c64bdeb2e877511632db8f       10               1.0          10
         6   0011e0d4e6b944f998e987f904e8c1e5        8               1.0          20
         7   0011e0d4e6b944f998e987f904e8c1e5        6               1.0           7
         10  0011e0d4e6b944f998e987f904e8c1e5        2               1.0           5

             duration  reward  email  mobile  social  web    ...      offer_discount  \
         3          5       5      1       1       1    1    ...                   0
         4         10       2      1       1       1    1    ...                   1
         6         10       5      1       0       0    1    ...                   1
         7          7       3      1       1       1    1    ...                   1
         10         7       5      1       1       0    1    ...                   0

             offer_informational  age  became_member_on  gender   income  valid  \
         3                     0   33              1804       M  72000.0      1
```

```
        4                      0   33              1804       M  72000.0      1
        6                      0   40              1541       O  57000.0      1
        7                      0   40              1541       O  57000.0      1
        10                     0   40              1541       O  57000.0      1

            gender_f  gender_m  gender_o
        3          0         1         0
        4          0         1         0
        6          0         0         1
        7          0         0         1
        10         0         0         1

        [5 rows x 21 columns]
```

```
In [41]: merged_df.drop(columns=['became_member_on', 'gender', 'valid', 'offer_successful']).ilo
```

```
Out[41]:   offer_id  difficulty  duration  reward  email  mobile  social  web  \
        0         4          10         7       2      1       1       0    1
        1         9           0         4       0      1       1       0    1
        2         3           0         3       0      1       1       1    0
        3         1           5         5       5      1       1       1    1
        4        10          10        10       2      1       1       1    1

           offer_bogo  offer_discount  offer_informational  age   income  gender_f  \
        0           0               1                    0   33  72000.0         0
        1           0               0                    1   33  72000.0         0
        2           0               0                    1   33  72000.0         0
        3           1               0                    0   33  72000.0         0
        4           0               1                    0   33  72000.0         0

           gender_m  gender_o
        0         1         0
        1         1         0
        2         1         0
        3         1         0
        4         1         0
```

```
In [42]: merged_df.iloc[:,1].head()
         merged_df.iloc[:,10:].head()
```

```
Out[42]:    offer_bogo  offer_discount  offer_informational  age  became_member_on  \
        0           0               1                    0   33              1804
        1           0               0                    1   33              1804
        2           0               0                    1   33              1804
        3           1               0                    0   33              1804
        4           0               1                    0   33              1804

          gender   income  valid  gender_f  gender_m  gender_o
        0      M  72000.0      1         0         1         0
        1      M  72000.0      1         0         1         0
        2      M  72000.0      1         0         1         0
        3      M  72000.0      1         0         1         0
        4      M  72000.0      1         0         1         0
```

```
In [43]: merged_df.isnull().sum()
```

```
Out[43]: customer_id              0
         offer_id                 0
         offer_successful         0
         difficulty               0
         duration                 0
         reward                   0
         email                    0
         mobile                   0
         social                   0
         web                      0
         offer_bogo               0
         offer_discount           0
         offer_informational      0
         age                      0
         became_member_on         0
         gender                8066
         income                8066
         valid                    0
         gender_f                 0
         gender_m                 0
         gender_o                 0
         dtype: int64
```

5.0.6 Create a model function that would remove the gender field since dummy values had earlier been generated for the field, then fill missing values in the income field with the income mean value

```
In [50]: def create_model_data(df):
             '''
             Description: Create a function that would return the  return X variables and the pr
             Input
                 - merged_df
             output
             - two dataframes X and Y
                 X - return the collection of the merged data.
                 Y - return the unique offer types.
             '''
             #drop categorical culumns from the experiment dataset
             my_model = df.copy()
             model_df = my_model.drop(columns=['gender', 'valid'])
             #We want to look at only successful offers
```

```
        model_df = model_df.loc[model_df['offer_successful'] == 1]
        #fill the missing values with mean of the field (data cleaning and workingwith miss
        model_df['income'] = model_df['income'].fillna(model_df['income'].mean())
        #gat all th rows from the 3rd colmun, focus on the quantitative data
        X = model_df.iloc[:,3:]

        #The the labels of all Offers
        Y= model_df.offer_id


        return X, Y
```

```
In [51]: features, target_labels = create_model_data(merged_df)
         features.shape, target_labels.shape
```

```
Out[51]: ((24460, 16), (24460,))
```

```
In [52]: target_labels.head()
```

```
Out[52]: 3      1
         4     10
         6      8
         7      6
         10     2
         Name: offer_id, dtype: object
```

```
In [53]: features.head()
```

```
Out[53]:     difficulty  duration  reward  email  mobile  social  web  offer_bogo  \
         3            5         5       5      1       1       1    1           1
         4           10        10       2      1       1       1    1           0
         6           20        10       5      1       0       0    1           0
         7            7         7       3      1       1       1    1           0
         10           5         7       5      1       1       0    1           1

             offer_discount  offer_informational  age  became_member_on   income  \
         3                0                    0   33              1804  72000.0
         4                1                    0   33              1804  72000.0
         6                1                    0   40              1541  57000.0
         7                1                    0   40              1541  57000.0
         10               0                    0   40              1541  57000.0

             gender_f  gender_m  gender_o
         3          0         1         0
         4          0         1         0
         6          0         0         1
         7          0         0         1
         10         0         0         1
```

5.0.7 1. Using Random Forrest Classifier:

In using this algorithm, it allows us to recommend the best offers for other customers using divide-and-conquer approach. It is a highly accurate and robust method because of the number of decision trees participating in the process . It does not suffer from the overfitting problem, takes the average of all the predictions, and cancels out the biases.

It works in four steps:

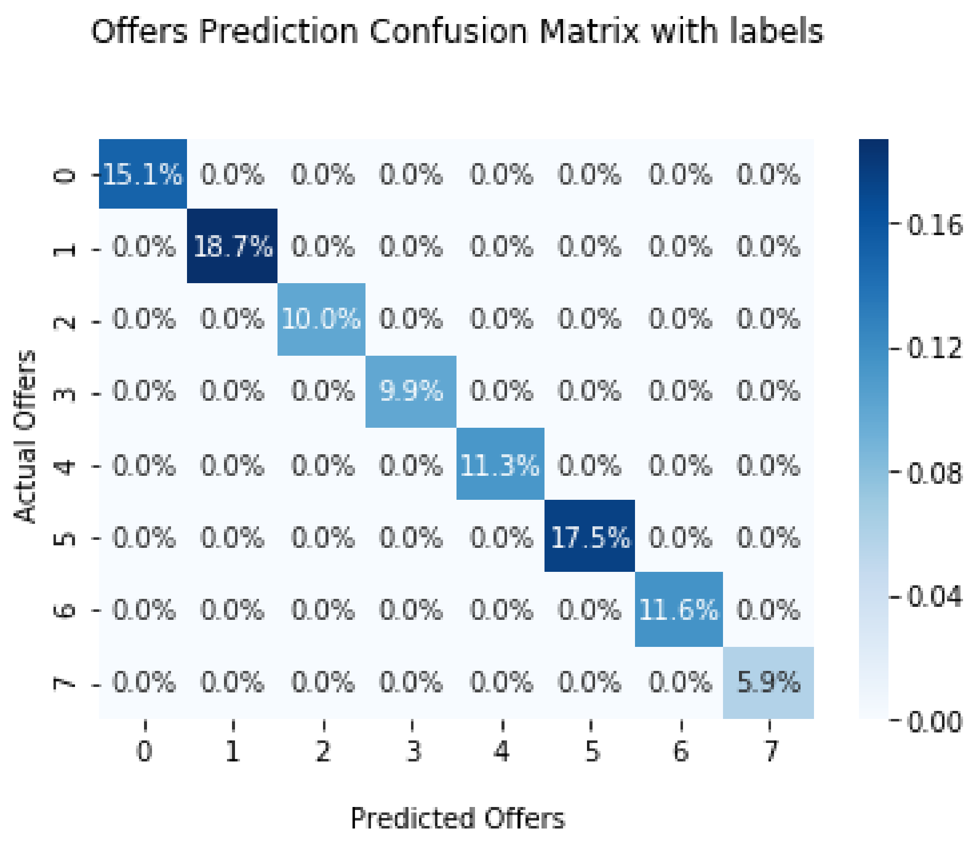
- Select random samples from a given dataset.
- Construct a decision tree for each sample and get a prediction result from each decision tree.
- Perform a vote for each predicted result.
- Select the prediction result with the most votes as the final prediction.

```
In [ ]:

In [54]: # Estimate the Scaling our inputs
         min_max_scaler = preprocessing.MinMaxScaler()
         X = min_max_scaler.fit_transform(features)

In [55]: #Use the experiment data to estimate the training and the test data sets
         X_train, X_test, y_train, y_test = \
         train_test_split(features,target_labels,test_size=.25,random_state=21)

         X_train.shape, X_test.shape

Out[55]: ((18345, 16), (6115, 16))

In [56]: # Scaling our inputs
         min_max_scaler2 = preprocessing.MinMaxScaler()
         X_train_fit = min_max_scaler2.fit_transform(X_train)
         X_test_fit = min_max_scaler2.fit_transform(X_test)

In [57]: #Create a Gaussian Classifier
         clf = RandomForestClassifier(n_estimators=100)
         clf.fit(X_train_fit,y_train)

Out[57]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=None, max_features='auto', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1,
                     oob_score=False, random_state=None, verbose=0,
                     warm_start=False)

In [58]: #Predict possible Offers using the test dataset
         y_pred=clf.predict(X_test_fit)

In [61]: y_pred

Out[61]: array(['2', '6', '10', ..., '6', '6', '1'], dtype=object)
```

5.0.8 Use Confusion Matrix to measure the accuracy of the prediction

- The Confuion Matrix allows us to visualize the performance of the classification machine learning models. With this visualization technique, we can get a better idea of how our machine learning model is performing
- We can look at a confusion matrix to see how much accurate classification and misclassification there was. The diagonal indicates correct % of classification. Off diagonals indicate the % of times the model misclassified an offer.

```
In [62]: #get the confusion matrix and the accuracy score
         confusion = confusion_matrix(y_test,y_pred)
         accuracy_score(y_test,y_pred)

Out[62]: 1.0

In [63]: confusion

Out[63]: array([[ 921,    0,    0,    0,    0,    0,    0,    0],
                [   0, 1145,    0,    0,    0,    0,    0,    0],
                [   0,    0,  612,    0,    0,    0,    0,    0],
                [   0,    0,    0,  607,    0,    0,    0,    0],
                [   0,    0,    0,    0,  691,    0,    0,    0],
                [   0,    0,    0,    0,    0, 1070,    0,    0],
                [   0,    0,    0,    0,    0,    0,  711,    0],
                [   0,    0,    0,    0,    0,    0,    0,  358]])

In [64]: ax = sns.heatmap(confusion/np.sum(confusion), annot=True, fmt='.1%', cmap='Blues')
         #ax = sns.heatmap(confusion,cmap='Blues')


         ax.set_title('Offers Prediction Confusion Matrix with labels\n\n');
         ax.set_xlabel('\nPredicted Offers')
         ax.set_ylabel('Actual Offers ');
         plt.figure(figsize = (25,20))

         ## Display the visualization of the Confusion Matrix.
         plt.show()
```



```
<matplotlib.figure.Figure at 0x7efcec9f35f8>
```

5.1 Using Model to classify individual gata groups

5.1.1 1. To determine which demographic group that responded best to each offer

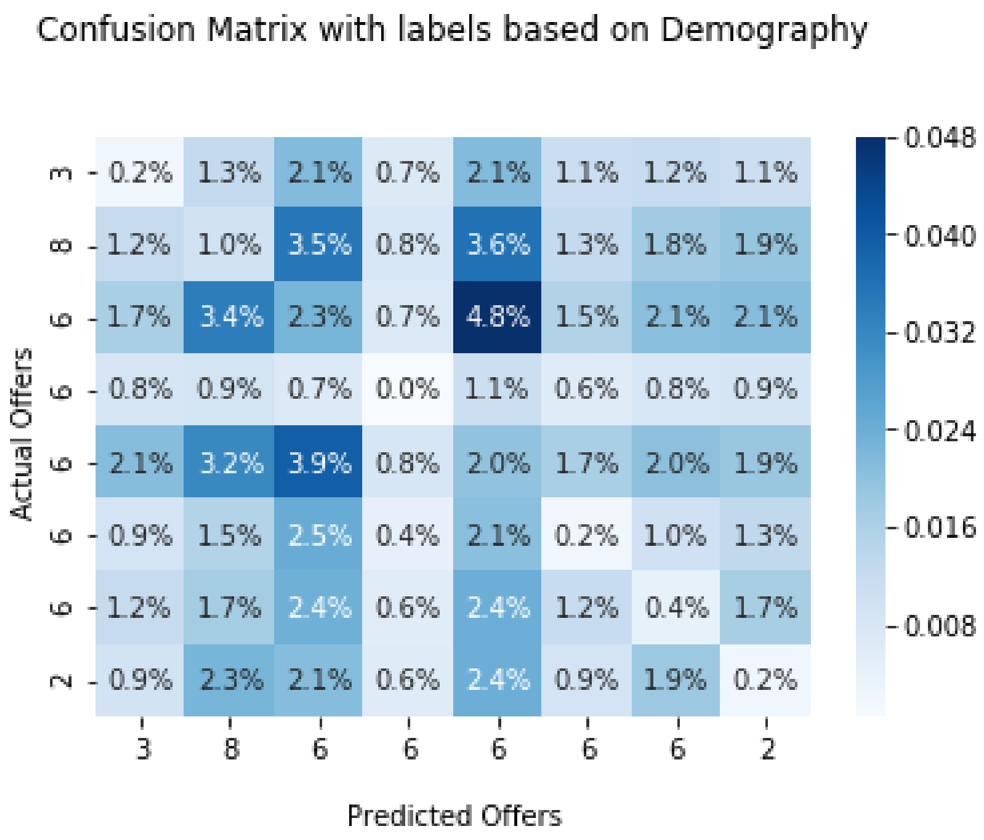
- Generate model data using the demographic collection

```
In [66]: X,Y = create_model_data(merged_df)

         #Only keep inforamtion in the X dataframe that refers to the user.
         X = X.iloc[:, 10:]
         X.head()

Out[66]:     age  became_member_on   income  gender_f  gender_m  gender_o
         3    33              1804  72000.0         0         1         0
         4    33              1804  72000.0         0         1         0
         6    40              1541  57000.0         0         0         1
         7    40              1541  57000.0         0         0         1
         10   40              1541  57000.0         0         0         1
```

```
In [67]: #Generate the train and test data for prediction
         X_train, X_test, y_train, y_test = train_test_split(\
                                 X,Y,test_size=.2,random_state=21)

         #Normalize the data
         sc = preprocessing .StandardScaler()
         X_train=sc.fit_transform(X_train)
         X_test = sc.fit_transform(X_test)

         #Instansiate Classifier
         classifier = RandomForestClassifier(n_estimators=100)


         #Train Classifier
         classifier.fit(X_train,y_train)

Out[67]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=None, max_features='auto', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1,
                     oob_score=False, random_state=None, verbose=0,
                     warm_start=False)

In [68]: y_pred = classifier.predict(X_test)

         print('Model accuracy: {0:0.2f}'.format(accuracy_score(y_test,y_pred)))
         print(classification_report(y_test,y_pred))

Model accuracy: 0.06
             precision    recall  f1-score   support

          1       0.06      0.05      0.05       737
         10       0.12      0.12      0.12       909
          2       0.04      0.03      0.03       485
          4       0.02      0.02      0.02       487
          5       0.02      0.02      0.02       554
          6       0.10      0.11      0.11       864
          7       0.03      0.03      0.03       571
          8       0.00      0.00      0.00       285

avg / total       0.06      0.06      0.06      4892


In [51]: #Generate the confusion matrix
         cf_matrix_std = confusion_matrix(y_test, y_pred)

In [52]: cf_matrix_std
```

```
Out[52]: array([[ 12,  62, 105,  33, 105,  54,  61,  53],
               [ 60,  47, 171,  39, 176,  62,  88,  94],
               [ 82, 166, 112,  35, 235,  75, 101, 103],
               [ 41,  44,  34,   2,  53,  30,  39,  42],
               [103, 155, 193,  41,  97,  82, 100,  93],
               [ 43,  74, 121,  22, 101,  12,  50,  64],
               [ 60,  85, 116,  29, 118,  59,  21,  83],
               [ 46, 112, 103,  30, 118,  43,  91,  11]])
```

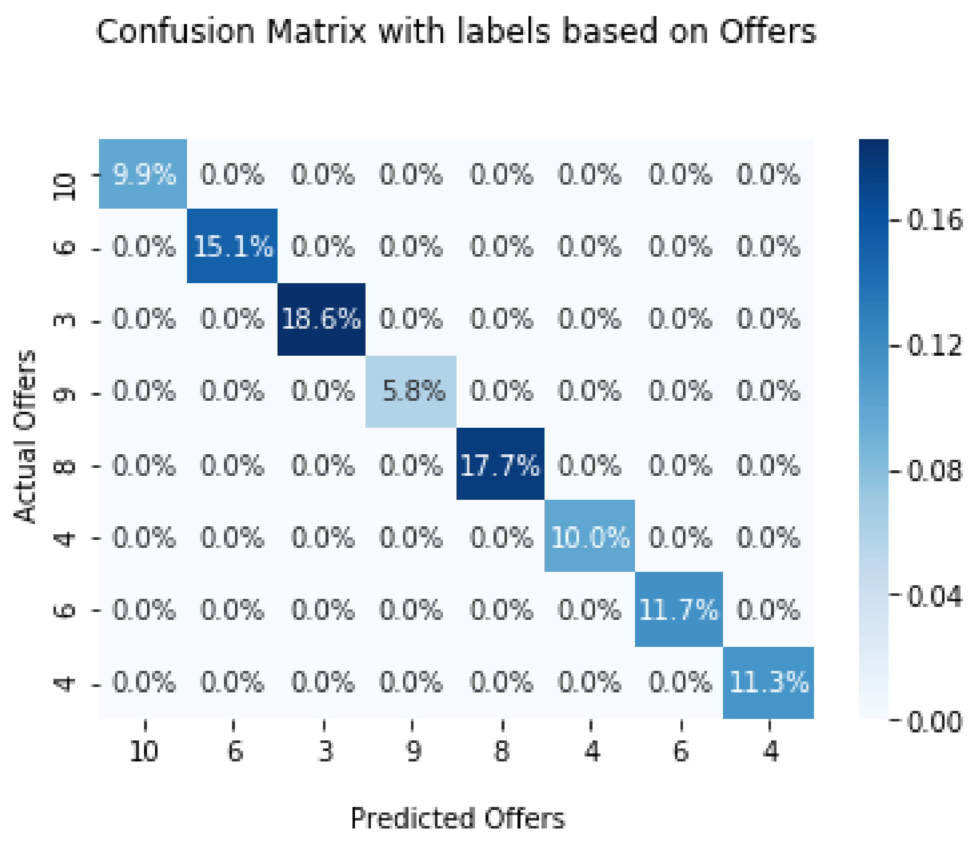
```
In [53]: ax = sns.heatmap(cf_matrix_std/np.sum(cf_matrix_std), annot=True, fmt='.1%', cmap='Blue
         ax.set_title('Confusion Matrix with labels based on Demography\n\n');
         ax.set_xlabel('\nPredicted Offers')
         ax.set_ylabel('Actual Offers ');
         ## Ticket labels - List must be in alphabetical order
         ax.xaxis.set_ticklabels(y_pred)
         ax.yaxis.set_ticklabels(y_pred)
         ## Display the visualization of the Confusion Matrix.
         plt.show()
```



5.1.2 To determine which Offer performed best among the offer types

```
In [54]: X,Y = create_model_data(merged_df)
In [59]: X = X.iloc[:, :10]
         X.head()

Out[59]:     difficulty  duration  reward  email  mobile  social  web  offer_bogo  \
         3            5         5       5      1       1       1    1           1
         4           10        10       2      1       1       1    1           0
         6           20        10       5      1       0       0    1           0
         7            7         7       3      1       1       1    1           0
         10           5         7       5      1       1       0    1           1

             offer_discount  offer_informational
         3                0                    0
         4                1                    0
         6                1                    0
         7                1                    0
         10               0                    0

In [60]: #Generate the train and test data for prediction
         X_train, X_test, y_train, y_test = train_test_split(X,Y,test_size=.2,random_state=21)

         #Normalize the data
         sc = preprocessing.StandardScaler()
         X_train=sc.fit_transform(X_train)
         X_test = sc.fit_transform(X_test)

         #Instansiate Classifier
         classifier = RandomForestClassifier(n_estimators=20,criterion='entropy',random_state=42


         #Train Classifier
         classifier.fit(X_train,y_train)

Out[60]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='entropy',
                     max_depth=None, max_features='auto', max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=20, n_jobs=1,
                     oob_score=False, random_state=42, verbose=0, warm_start=False)

In [61]: y_pred = classifier.predict(X_test)

         print('Model accuracy: {0:0.2f}'.format(accuracy_score(y_test,y_pred)))
         print(classification_report(y_test,y_pred))

Model accuracy: 1.00
             precision    recall  f1-score   support

         10       1.00      1.00      1.00       485
          2       1.00      1.00      1.00       737
          3       1.00      1.00      1.00       909
          4       1.00      1.00      1.00       285
          6       1.00      1.00      1.00       864
          7       1.00      1.00      1.00       487
          8       1.00      1.00      1.00       571
          9       1.00      1.00      1.00       554

avg / total       1.00      1.00      1.00      4892
```

```
In [62]: #Generate the confusion matrix
         cf_matrix_std_offers = confusion_matrix(y_test, y_pred)

In [63]: cf_matrix_std_offers

Out[63]: array([[485,   0,   0,   0,   0,   0,   0,   0],
                [  0, 737,   0,   0,   0,   0,   0,   0],
                [  0,   0, 909,   0,   0,   0,   0,   0],
                [  0,   0,   0, 285,   0,   0,   0,   0],
                [  0,   0,   0,   0, 864,   0,   0,   0],
                [  0,   0,   0,   0,   0, 487,   0,   0],
                [  0,   0,   0,   0,   0,   0, 571,   0],
                [  0,   0,   0,   0,   0,   0,   0, 554]])

In [64]: ax = sns.heatmap(cf_matrix_std_offers/np.sum(cf_matrix_std_offers), annot=True, fmt='.1
         ax.set_title('Confusion Matrix with labels based on Offers\n\n');
         ax.set_xlabel('\nPredicted Offers')
         ax.set_ylabel('Actual Offers ');
         ## Ticket labels - List must be in alphabetical order
         ax.xaxis.set_ticklabels(y_pred)
         ax.yaxis.set_ticklabels(y_pred)
         ## Display the visualization of the Confusion Matrix.
         plt.show()
```



5.1.3 Using Logistic Regression

- Gradient Boosting uses an ensemble of decision trees to predict a target label. However, unlike AdaBoost, the Gradient Boost trees have a depth larger than 1
- Calculate the average of the target label
- Calculate the residuals: For every sample, we calculate the residual with the proceeding formula.
- residual = actual value – predicted value
- Construct a decision tree
- Predict the target label using all of the trees within the ensemble
- Once trained, use all of the trees in the ensemble to make a final prediction as to the value of the target variable

5.1.4 Use GridSearchCV to discover optimal parameters

https://www.kaggle.com/enespolat/grid-search-with-logistic-regression https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html

```
In [69]: #create a model_pipeline
         def model_pipeline(X_features, y_target):
             '''
```

```
        inputs:
        - X_features & y_target dataframe

        outputs:
        - Splits features and target dataframe to train and test sets, performs feature sca
        - Outputs X_train, X_test, y_train and y_test dataframes
        '''

        #split into training and test sets
        X_train, X_test, y_train, y_test = train_test_split(X_features,y_target, test_size=

        #fit and transform scaling on training data
        scaler= preprocessing.StandardScaler()
        X_train=scaler.fit_transform(X_train)

        #scale test data
        X_test=scaler.transform(X_test)

        return X_train,X_test,y_train, y_test
```

```
In [70]: #define Grid Search function
         def grid_search_random_forest(X,y):
             '''
             input:
             - X,y: training datasets for X and y
             output:
             - dictionary with best parameters for random forest model
             '''

             params={'max_features': ['auto', 'sqrt'],
                          'max_depth' : [5,10,15,20],
                          'n_estimators': [20,30,40,50],
                          'min_samples_split': [2, 10, 20],
                          'min_samples_leaf': [2, 10,15, 20],
                          }
             gs_cv = GridSearchCV(RandomForestClassifier(random_state=2), params)
             gs_cv.fit(X, y)
             gs_cv.best_params_

             return gs_cv.best_params_
```

```
In [77]: # Split the dataset into training and test dataset
         X,Y = create_model_data(merged_df)
         x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state=1)

         # Create a Logistic Regression Object, perform Logistic Regression
         #using some information from
         #https://www.kaggle.com/code/enespolat/grid-search-with-logistic-regression/notebook
```

```
#https://www.datarmatics.com/data-science/how-to-perform-logistic-regression-in-pythons

params = {
    'penalty': ['l1','l2'],
    'C': [1,10,100,1000]
}

grid_cv = GridSearchCV(LogisticRegression(C=1.0, class_weight=None, dual=False, fit_int
                   intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                   penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                   verbose=3, warm_start=False), params, verbose=3, n_jobs=-1,cv=3)
```

```
In [78]: grid_cv.fit(x_train, y_train)
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits
[CV] C=1, penalty=l1 ...
[LibLinear][CV] ... C=1, penalty=l1, score=1.0, total=   0.9s
[CV] C=1, penalty=l1 ...
[LibLinear]

[Parallel(n_jobs=-1)]: Done   1 out of   1 | elapsed:    0.9s remaining:    0.0s


[CV] ... C=1, penalty=l1, score=1.0, total=   0.9s
[CV] C=1, penalty=l1 ...
[LibLinear]

[Parallel(n_jobs=-1)]: Done   2 out of   2 | elapsed:    1.8s remaining:    0.0s


[CV] ... C=1, penalty=l1, score=1.0, total=   0.9s
[CV] C=1, penalty=l2 ...
[LibLinear][CV] ... C=1, penalty=l2, score=0.9344557044785877, total=   1.2s
[CV] C=1, penalty=l2 ...
[LibLinear][CV] ... C=1, penalty=l2, score=0.8220477592410861, total=   1.2s
[CV] C=1, penalty=l2 ...
[LibLinear][CV] ... C=1, penalty=l2, score=0.891542614101096, total=   1.2s
[CV] C=10, penalty=l1 ...
[LibLinear][CV] ... C=10, penalty=l1, score=1.0, total=   0.6s
[CV] C=10, penalty=l1 ...
[LibLinear][CV] ... C=10, penalty=l1, score=1.0, total=   0.6s
[CV] C=10, penalty=l1 ...
[LibLinear][CV] ... C=10, penalty=l1, score=1.0, total=   0.7s
[CV] C=10, penalty=l2 ...
[LibLinear][CV] ... C=10, penalty=l2, score=0.9382151029748284, total=   1.2s
[CV] C=10, penalty=l2 ...
[LibLinear][CV] ... C=10, penalty=l2, score=0.8544324501144913, total=   1.3s
[CV] C=10, penalty=l2 ...
[LibLinear][CV] ... C=10, penalty=l2, score=0.8378864714542777, total=   1.1s
```

```
[CV] C=100, penalty=l1 ...
[LibLinear][CV] ... C=100, penalty=l1, score=1.0, total=   0.7s
[CV] C=100, penalty=l1 ...
[LibLinear][CV] ... C=100, penalty=l1, score=1.0, total=   0.6s
[CV] C=100, penalty=l1 ...
[LibLinear][CV] ... C=100, penalty=l1, score=1.0, total=   0.5s
[CV] C=100, penalty=l2 ...
[LibLinear][CV] ... C=100, penalty=l2, score=0.9488394900294214, total=   1.2s
[CV] C=100, penalty=l2 ...
[LibLinear][CV] ... C=100, penalty=l2, score=0.8609748119070985, total=   1.3s
[CV] C=100, penalty=l2 ...
[LibLinear][CV] ... C=100, penalty=l2, score=0.8885980696875512, total=   1.1s
[CV] C=1000, penalty=l1 ...
[LibLinear][CV] ... C=1000, penalty=l1, score=1.0, total=   0.6s
[CV] C=1000, penalty=l1 ...
[LibLinear][CV] ... C=1000, penalty=l1, score=1.0, total=   0.6s
[CV] C=1000, penalty=l1 ...
[LibLinear][CV] ... C=1000, penalty=l1, score=1.0, total=   0.7s
[CV] C=1000, penalty=l2 ...
[LibLinear][CV] ... C=1000, penalty=l2, score=0.940339980385747, total=   1.2s
[CV] C=1000, penalty=l2 ...
[LibLinear][CV] ... C=1000, penalty=l2, score=0.8132155708210664, total=   1.2s
[CV] C=1000, penalty=l2 ...
[LibLinear][CV] ... C=1000, penalty=l2, score=0.8845084246687388, total=   1.1s
[LibLinear]

[Parallel(n_jobs=-1)]: Done  24 out of  24 | elapsed:   23.0s finished
```

```
Out[78]: GridSearchCV(cv=3, error_score='raise',
                estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept
                   intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                   penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                   verbose=3, warm_start=False),
                fit_params=None, iid=True, n_jobs=-1,
                param_grid={'penalty': ['l1', 'l2'], 'C': [1, 10, 100, 1000]},
                pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                scoring=None, verbose=3)
```

```
In [79]: grid_cv.best_params_
```

```
Out[79]: {'C': 1, 'penalty': 'l1'}
```

```
In [80]: logistic_y_pred = grid_cv.predict(x_test)
         logistic_accuracy = accuracy_score(y_test,logistic_y_pred)
         #logistic_f1 = f1_score(y_test,logistic_y_pred)
```

```
In [81]: accuracy_score(y_test, logistic_y_pred)
```

```
Out[81]: 1.0
```

```
In [82]: #y_pred = log_model.predict(X_test)
         conf_matrix = confusion_matrix(y_test, logistic_y_pred)
         print(classification_report(y_test, logistic_y_pred))
         print(confusion_matrix(y_test, logistic_y_pred))
         print(accuracy_score(y_test, logistic_y_pred))

         print("tuned hpyerparameters :(best parameters) ", grid_cv.best_params_)
         print("accuracy :",grid_cv.best_score_)
```

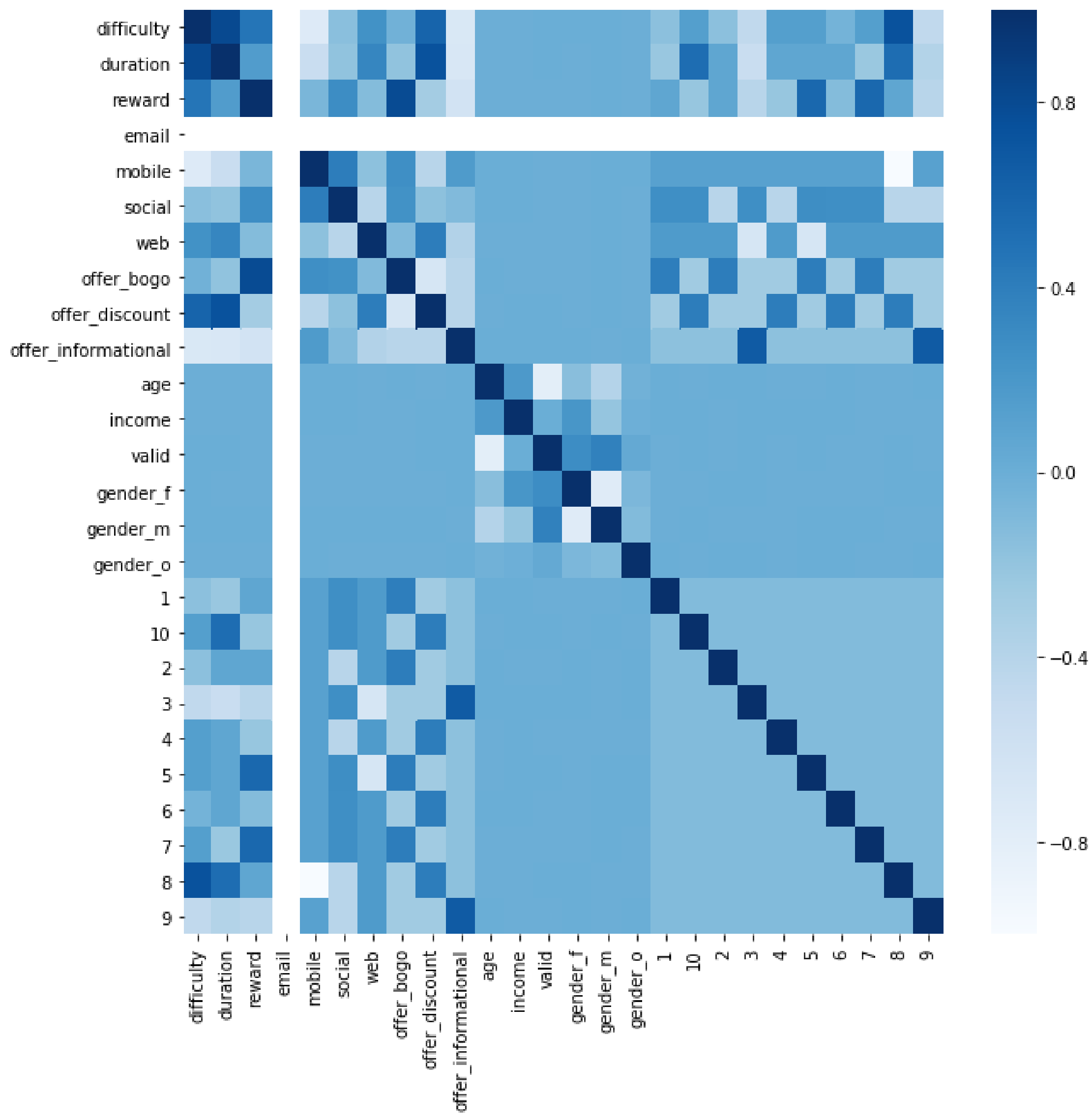
```
             precision    recall  f1-score   support

          1       1.00      1.00      1.00       919
         10       1.00      1.00      1.00      1098
          2       1.00      1.00      1.00       610
          4       1.00      1.00      1.00       603
          5       1.00      1.00      1.00       713
          6       1.00      1.00      1.00      1066
          7       1.00      1.00      1.00       748
          8       1.00      1.00      1.00       358

avg / total       1.00      1.00      1.00      6115

[[ 919    0    0    0    0    0    0    0]
 [    0 1098    0    0    0    0    0    0]
 [    0    0  610    0    0    0    0    0]
 [    0    0    0  603    0    0    0    0]
 [    0    0    0    0  713    0    0    0]
 [    0    0    0    0    0 1066    0    0]
 [    0    0    0    0    0    0  748    0]
 [    0    0    0    0    0    0    0  358]]
1.0
tuned hpyerparameters :(best parameters)  {'C': 1, 'penalty': 'l1'}
accuracy : 1.0
```

5.1.5 Convert categorical variable, offer ids designated as labels 1 - 10) into dummy/indicator variables. This would enable us understand how the offered performed across transactions and demography.

```
In [97]: #Clean the income columns by filling Nan values with mean of the incomes
         merged_df['income'] = merged_df['income'].fillna(merged_df['income'].mean())
         X = merged_df.iloc[:,3:] #get all rows that represent quantitative data
         y = merged_df.offer_successful #get all rows for offer_successful status

         X = pd.concat([X, merged_df['offer_id']],axis=1)
```

```
In [98]: dummies = pd.get_dummies(X['offer_id'])
         adjusted = X.drop(['offer_id', 'gender', 'became_member_on'],axis=1)
         merged_new = pd.concat([adjusted, dummies],axis=1)
```

```
In [99]: merged_new.head()

Out[99]:    difficulty  duration  reward  email  mobile  social  web  offer_bogo  \
         0          10         7       2      1       1       0    1           0
         1           0         4       0      1       1       0    1           0
         2           0         3       0      1       1       1    0           0
         3           5         5       5      1       1       1    1           1
         4          10        10       2      1       1       1    1           0

            offer_discount  offer_informational ...  1  10  2  3  4  5  6  7  8  9
         0               1                    0 ...  0   0  0  0  1  0  0  0  0  0
         1               0                    1 ...  0   0  0  0  0  0  0  0  0  1
         2               0                    1 ...  0   0  0  1  0  0  0  0  0  0
         3               0                    0 ...  1   0  0  0  0  0  0  0  0  0
         4               1                    0 ...  0   1  0  0  0  0  0  0  0  0

         [5 rows x 26 columns]

In [103]: plt.figure(figsize=(10,10))
          # calculate the correlation matrix
          corr = merged_new.corr()

          # plot the heatmap
          #https://stackoverflow.com/questions/39409866/correlation-heatmap
          sns.heatmap(corr,
              xticklabels=merged_new.columns,
              yticklabels=merged_new.columns,
              fmt='.1%', cmap='Blues')

Out[103]: <matplotlib.axes._subplots.AxesSubplot at 0x7efcd2640dd8>
```



```
In [104]: #From the above diagram, there is a correlation on the email attribute.
          #This is because all customers that participated in the offers had their email address
          #so let's drop the email field
          X = merged_new.drop(['email'], axis=1)
          X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=.2, random_state =

          scaler = preprocessing.MinMaxScaler()

In [105]: X_train.head()

Out[105]:        difficulty  duration  reward  mobile  social  web  offer_bogo  \
          15937          10         7       2       1       0    1           0
          15639          10         7      10       1       1    0           1
```

```
25222          10         7       2       1       0    1           0
13047          10         7       2       1       0    1           0
2561           10         5      10       1       1    1           1

       offer_discount  offer_informational  age ...  1  10  2  3  4  5  6  7  \
15937               1                    0   84 ...  0   0  0  0  1  0  0  0
15639               0                    0  118 ...  0   0  0  0  0  1  0  0
25222               1                    0   67 ...  0   0  0  0  1  0  0  0
13047               1                    0   56 ...  0   0  0  0  1  0  0  0
2561                0                    0   90 ...  0   0  0  0  0  0  0  1

       8  9
15937  0  0
15639  0  0
25222  0  0
13047  0  0
2561   0  0

[5 rows x 25 columns]
```

```
In [91]: X_train = scaler.fit_transform(X_train)

         X_test = scaler.fit_transform(X_test)
         logistic_model = LogisticRegression(solver='liblinear',random_state=42)
```

```
In [92]: logistic_model.fit(X_train,y_train)
         logistic_y_pred = logistic_model.predict(X_test)
         logistic_accuracy = accuracy_score(y_test,logistic_y_pred)

         print("Logistic Regression Accuracy: %.2f" % accuracy_score(y_test, logistic_y_pred))
```

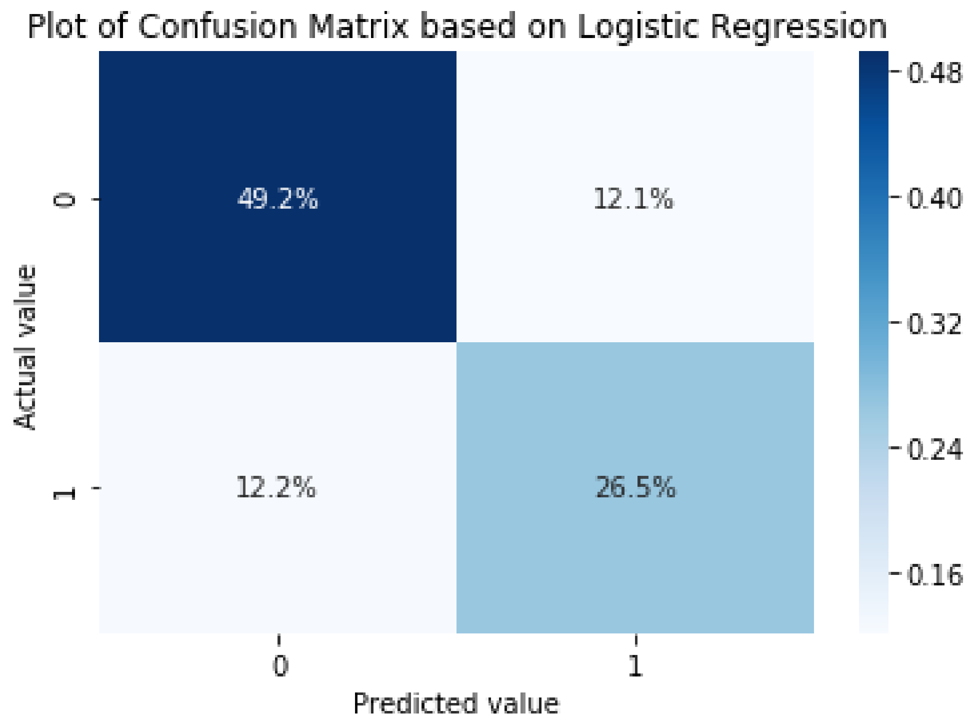
```
Logistic Regression Accuracy: 0.76
```

```
In [93]: #Calculate the confusion matrix
         confusion = confusion_matrix(y_test,logistic_y_pred)
```

```
In [116]: print(confusion/np.sum(confusion))
```

```
[[ 0.49178385  0.12055617]
 [ 0.1224522   0.26520777]]
```

```
In [114]: sns.heatmap(confusion/np.sum(confusion),annot=True, fmt='.1%', cmap='Blues')
          plt.title('Plot of Confusion Matrix based on Logistic Regression')
          plt.ylabel("Actual value")
          plt.xlabel("Predicted value");
```



```
In [96]: #calculate the F1 Score
         logistic_f1 = f1_score(y_test,logistic_y_pred)
         print("F1 Score for the Logistic Regression modle is: %.2f" % logistic_f1)
```

```
F1 Score for the Logistic Regression modle is: 0.69
```

Reapply the GridSearchCV Algorithm based on the Logistic Regression trained data

```
In [106]: grid_cv2 = GridSearchCV(LogisticRegression(C=1.0, class_weight=None, dual=False, fit_i
                                  intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                                  penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                                  verbose=3, warm_start=False), params, verbose=3, n_jobs=-1,cv=3)
```

```
In [109]: grid_cv2.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits
[CV] C=1, penalty=l1 ...
[LibLinear][CV] ... C=1, penalty=l1, score=0.7558807844996148, total=   0.4s
[CV] C=1, penalty=l1 ...
[LibLinear]

[Parallel(n_jobs=-1)]: Done   1 out of   1 | elapsed:    0.4s remaining:    0.0s
```

```
[CV] ... C=1, penalty=l1, score=0.7519108846358951, total=   0.3s
[CV] C=1, penalty=l1 ...
[LibLinear]

[Parallel(n_jobs=-1)]: Done   2 out of   2 | elapsed:    0.6s remaining:    0.0s


[CV] ... C=1, penalty=l1, score=0.7453187959232046, total=   0.5s
[CV] C=1, penalty=l2 ...
[LibLinear][CV] ... C=1, penalty=l2, score=0.592937133376785, total=   0.2s
[CV] C=1, penalty=l2 ...
[LibLinear][CV] ... C=1, penalty=l2, score=0.5902707827220478, total=   0.3s
[CV] C=1, penalty=l2 ...
[LibLinear][CV] ... C=1, penalty=l2, score=0.5916093861104527, total=   0.3s
[CV] C=10, penalty=l1 ...
[LibLinear][CV] ... C=10, penalty=l1, score=0.7559992889731587, total=   0.4s
[CV] C=10, penalty=l1 ...
[LibLinear][CV] ... C=10, penalty=l1, score=0.7512591100314037, total=   0.3s
[CV] C=10, penalty=l1 ...
[LibLinear][CV] ... C=10, penalty=l1, score=0.7455558189144347, total=   0.2s
[CV] C=10, penalty=l2 ...
[LibLinear][CV] ... C=10, penalty=l2, score=0.592937133376785, total=   0.2s
[CV] C=10, penalty=l2 ...
[LibLinear][CV] ... C=10, penalty=l2, score=0.5902707827220478, total=   0.3s
[CV] C=10, penalty=l2 ...
[LibLinear][CV] ... C=10, penalty=l2, score=0.5916093861104527, total=   0.3s
[CV] C=100, penalty=l1 ...
[LibLinear][CV] ... C=100, penalty=l1, score=0.7545179830538603, total=   0.2s
[CV] C=100, penalty=l1 ...
[LibLinear][CV] ... C=100, penalty=l1, score=0.7520886413462108, total=   0.2s
[CV] C=100, penalty=l1 ...
[LibLinear][CV] ... C=100, penalty=l1, score=0.7453780516710121, total=   0.4s
[CV] C=100, penalty=l2 ...
[LibLinear][CV] ... C=100, penalty=l2, score=0.592937133376785, total=   0.2s
[CV] C=100, penalty=l2 ...
[LibLinear][CV] ... C=100, penalty=l2, score=0.5902707827220478, total=   0.3s
[CV] C=100, penalty=l2 ...
[LibLinear][CV] ... C=100, penalty=l2, score=0.5916093861104527, total=   0.3s
[CV] C=1000, penalty=l1 ...
[LibLinear][CV] ... C=1000, penalty=l1, score=0.7559400367363868, total=   0.4s
[CV] C=1000, penalty=l1 ...
[LibLinear][CV] ... C=1000, penalty=l1, score=0.7514961189784914, total=   0.4s
[CV] C=1000, penalty=l1 ...
[LibLinear][CV] ... C=1000, penalty=l1, score=0.7452002844275895, total=   0.5s
[CV] C=1000, penalty=l2 ...
[LibLinear][CV] ... C=1000, penalty=l2, score=0.592937133376785, total=   0.3s
[CV] C=1000, penalty=l2 ...
[LibLinear][CV] ... C=1000, penalty=l2, score=0.5902707827220478, total=   0.3s
```

```
[CV] C=1000, penalty=l2 ...
[LibLinear][CV] ... C=1000, penalty=l2, score=0.5916093861104527, total=   0.3s
[LibLinear]

[Parallel(n_jobs=-1)]: Done  24 out of  24 | elapsed:    7.3s finished
```

```
Out[109]: GridSearchCV(cv=3, error_score='raise',
                 estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercep
                    intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                    penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                    verbose=3, warm_start=False),
                 fit_params=None, iid=True, n_jobs=-1,
                 param_grid={'penalty': ['l1', 'l2'], 'C': [1, 10, 100, 1000]},
                 pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                 scoring=None, verbose=3)
```

```
In [110]: grid_cv2.best_params_
```

```
Out[110]: {'C': 1, 'penalty': 'l1'}
```

```
In [111]: logistic_y_pred2 = grid_cv2.predict(X_test)
          logistic_accuracy2 = accuracy_score(y_test,logistic_y_pred2)
          logistic_f12 = f1_score(y_test,logistic_y_pred2)
```

```
In [112]: #Generate the Confusion matrix
          conf_matrix2 = confusion_matrix(y_test, logistic_y_pred2)


          print("See the classification report below:")
          print(classification_report(y_test, logistic_y_pred2))
          print("See the confusion matric below:")
          print(conf_matrix2)
          print("The accuracy from Logistic Regression using Grid Serch CV is: ", logistic_accur

          print("Logistic Regression :(best parameters) ", grid_cv2.best_params_)
          print("Logistic Regression accuracy :",grid_cv2.best_score_)
```

```
See the classification report below:
             precision    recall  f1-score   support

        0.0       0.80      0.80      0.80      7751
        1.0       0.69      0.68      0.69      4907

avg / total       0.76      0.76      0.76     12658

See the confusion matric below:
[[6224 1527]
 [1555 3352]]
```

```
The accuracy from Logistic Regression using Grid Serch CV is:  0.756517617317
Logistic Regression :(best parameters)  {'C': 1, 'penalty': 'l1'}
Logistic Regression accuracy : 0.751036934624
```

```
In [295]: #Confusion Matrix expressed as a percentage
          percent_conf = conf_matrix2/np.sum(conf_matrix2)
```

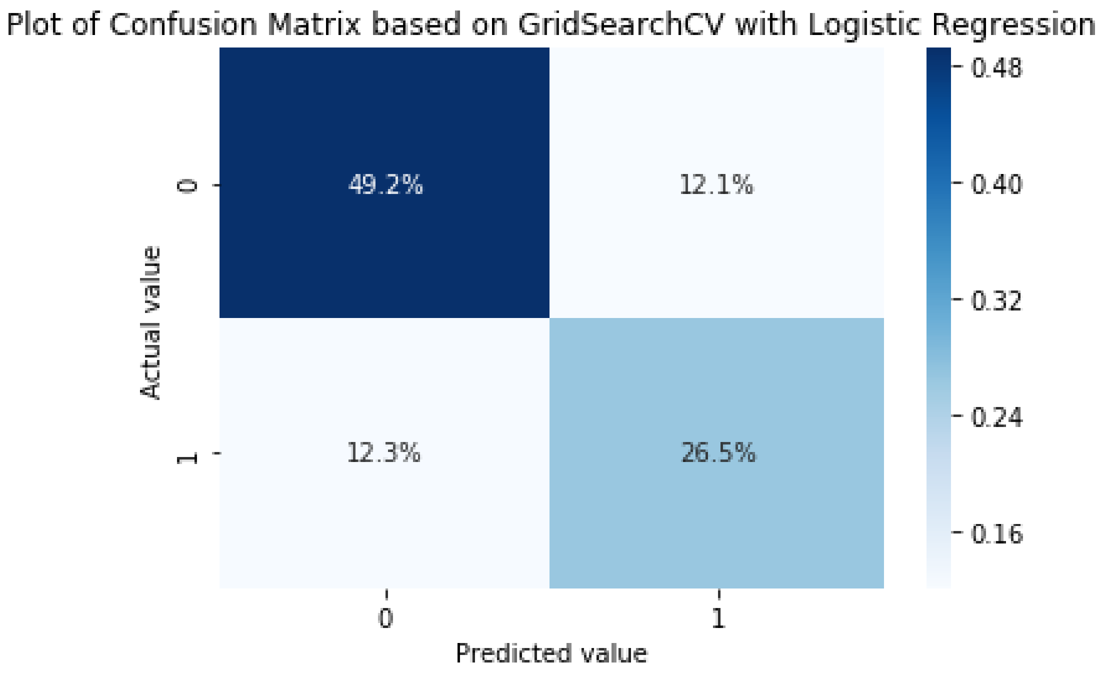
```
In [298]: print("See the confusion matric below: (%)")
          print(percent_conf)
```

```
See the confusion matric below: (%)
[[ 0.49138884  0.12095118]
 [ 0.1224522   0.26520777]]
```

```
In [299]: print("Logistic Regression FI Score :",logistic_f12)
```

```
Logistic Regression FI Score : 0.685451761103
```

```
In [113]: sns.heatmap(conf_matrix2/np.sum(conf_matrix2),annot=True, fmt='.1%', cmap='Blues')
          plt.title('Plot of Confusion Matrix based on GridSearchCV with Logistic Regression')
          plt.ylabel("Actual value")
          plt.xlabel("Predicted value");
```



```
In [ ]:
```