Machine Learning Engineer Nanodegree

Starbucks Capstone Challenge

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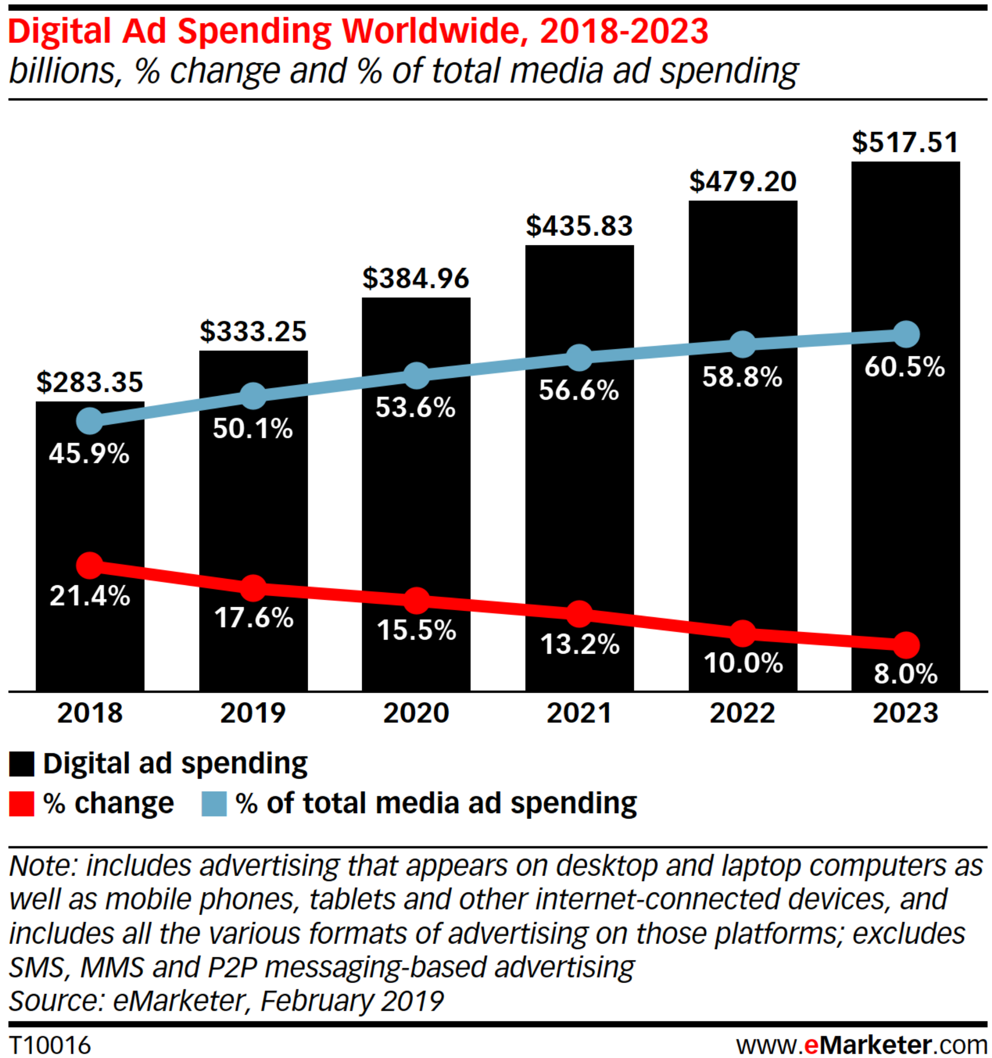
I. Definition

Project Overview

Domain Background

Marketing is all about getting 4 things **right** – reaching out to the **right** customer with the **right** product at the **right** time through the right channel. While the change in information consumption has resulted in digital marketing taking over the traditional marketing, Data Science has revolutionized and reshaped the digital advertisement business to meet those objectives.



The use cases range from capitalizing on unexpected insights, boosting contextual relevance to generate response from target audience, defining optimum pricing based on demographics, enhancing ads creativity based on various segments to generate response, and much more..

Introduction

I chose the data provided by Starbuck for this final capstone project. 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.

The 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.

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.

Cleaning

This makes data cleaning especially important and tricky.

I also have 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.

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

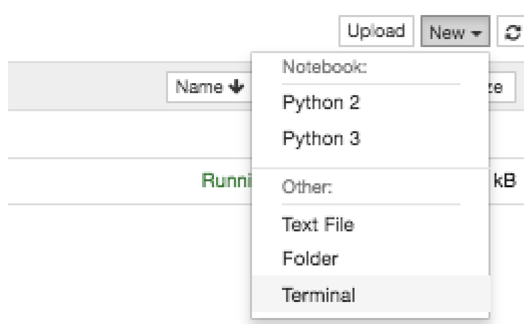
- age (int) - age of the customer
- became_member_on (int) - date when customer created an app account
- gender (str) - gender of the customer (note some entries contain 'O' for other rather than M or F)
- id (str) - customer id
- income (float) - customer's income

transcript.json

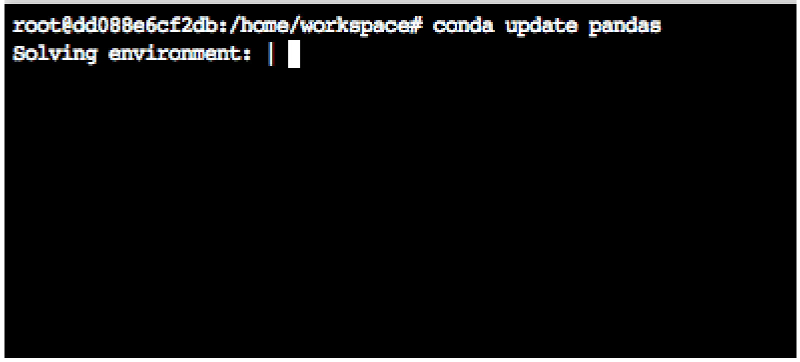
- event (str) - record description (ie transaction, offer received, offer viewed, etc.)
- person (str) - customer id
- time (int) - time in hours since start of test. The data begins at time t=0
- value - (dict of strings) - either an offer id or transaction amount depending on the record

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.

Problem Statement

In this project we will explore the data provided by Starbucks as explain above.

The goal in this project is to build a model that predicts whether someone will respond to an offer or not. This should help in defining which offer should be sent to a certain customer triggering more revenue. Also, various demographics groups and offer type relation might be identified.

Below are the tasks that will be executed to achieve the objectives:

- Data Exploration and Analysis.
- Data pre-processing, Feature engineering and selection.
- Data preperation for Machine Learning
- Model Training
- Fine Tuning
- Solution

Metrics

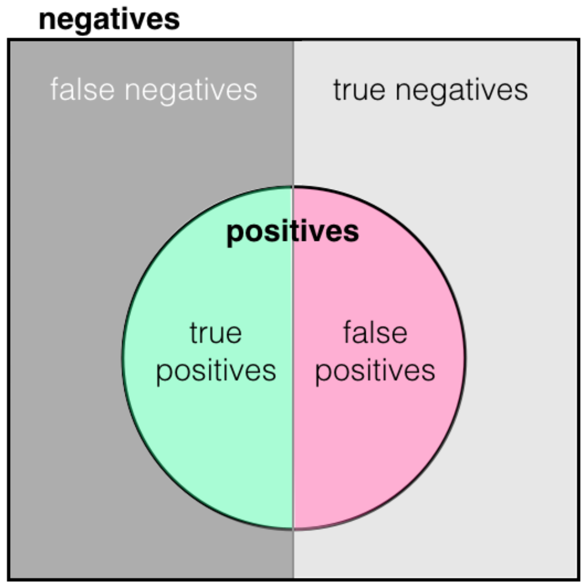
Reference : [https://towardsdatascience.com/beyond-accuracy-precision-and-recall-3da06bea9f6c (https://towardsdatascience.com/beyond-accuracy-precision-and-recall-3da06bea9f6c)](https://towardsdatascience.com/beyond-accuracy-precision-and-recall-3da06bea9f6c)

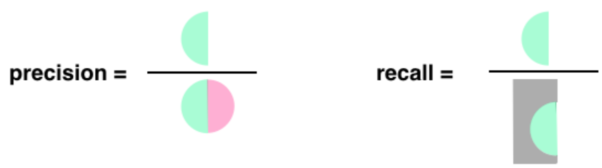
Precision and recall are just different metrics for measuring the "success" or performance of a trained model.

Precision, also called as accuracy of positive predictions, is defined as the number of true positives over all positives, and will be the higher when the amount of false positives is low.

Recall, also called sensitivity or True positive rate, is defined as the number of true positives over true positives plus false negatives and will be higher when the number of false negatives is low.

Both take into account true positives and will be higher for high, positive accuracy, too.





It is often convenient to combine precision and recall into a single metric called the F1 score, in particular if you need a simple way to compare two classifiers. The F score is the harmonic mean of precision and recall whereas the regular mean treats all values equally, the harmonic mean givesmuch more weight to low values. As a result, the classifier will only get a high F1 score if both recall and precision are high.

II. Analysis

Data Exploration

Exploratory Visualization

Reference: [https://machinelearningmastery.com/understand-problem-get-better-results-using-exploratory-data-analysis/ (https://machinelearningmastery.com/understand-problem-get-better-results-using-exploratory-data-analysis/)](https://machinelearningmastery.com/understand-problem-get-better-results-using-exploratory-data-analysis/)

In [1]:
```
#General Packages
import math
import json
import os
import datetime

#Import PyData packages
import pandas as pd
import numpy as np
% matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns

#Sklearn Packages
from sklearn.preprocessing import MultiLabelBinarizer, StandardScaler, Imputer
from sklearn.model_selection import train_test_split
from sklearn import metrics

import warnings
from sklearn.exceptions import DataConversionWarning
warnings.filterwarnings(action='ignore', category=DataConversionWarning)

import boto3
import sagemaker
```

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)

print("portfolio Columns : ", portfolio.columns.tolist())
print("profile Columns : ", profile.columns.tolist())
print("transcript Columns : ", transcript.columns.tolist())
```

```
portfolio Columns :  ['channels', 'difficulty', 'duration', 'id', 'offer_type',
'reward']
profile Columns :  ['age', 'became_member_on', 'gender', 'id', 'income']
transcript Columns :  ['event', 'person', 'time', 'value']
```

In [3]:
```
#Renames the column to remove disambiguation and making column more descriptive.
portfolio.rename(columns={"id": "offer_id"}, inplace = True)
portfolio.head(10)
```

Out[3]:

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

In [4]:
```
#Renames the column to remove disambiguation.
profile.rename(columns={"id": "customer_id"}, inplace = True)
profile.head(10)
```

Out[4]:

	age	became_member_on	gender	customer_id	income
0	118	20170212	None	68be06ca386d4c31939f3a4f0e3dd783	NaN
1	55	20170715	F	0610b486422d4921ae7d2bf64640c50b	112000.0
2	118	20180712	None	38fe809add3b4fcf9315a9694bb96ff5	NaN
3	75	20170509	F	78afa995795e4d85b5d9ceeca43f5fef	100000.0
4	118	20170804	None	a03223e636434f42ac4c3df47e8bac43	NaN
5	68	20180426	M	e2127556f4f64592b11af22de27a7932	70000.0
6	118	20170925	None	8ec6ce2a7e7949b1bf142def7d0e0586	NaN
7	118	20171002	None	68617ca6246f4fbc85e91a2a49552598	NaN
8	65	20180209	M	389bc3fa690240e798340f5a15918d5c	53000.0
9	118	20161122	None	8974fc5686fe429db53ddde067b88302	NaN

In [5]:
```
#Inspect portfolio dataset
print(portfolio.shape)
portfolio.info()
portfolio.head(10)
```

```
(10, 6)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 6 columns):
channels      10 non-null object
difficulty    10 non-null int64
duration      10 non-null int64
offer_id      10 non-null object
offer_type    10 non-null object
reward        10 non-null int64
dtypes: int64(3), object(3)
memory usage: 560.0+ bytes
```

Out[5]:

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

In [6]:
```
#Check count of various offer_type
portfolio["offer_type"].value_counts()
```

Out[6]:
```
discount         4
bogo             4
informational    2
Name: offer_type, dtype: int64
```

In [7]:
```
portfolio["difficulty"].value_counts()
```

Out[7]:
```
10    4
5     2
0     2
7     1
20    1
Name: difficulty, dtype: int64
```

In [8]:
```
portfolio["duration"].value_counts()
```

Out[8]:
```
7     4
10    2
5     2
4     1
3     1
Name: duration, dtype: int64
```

In [9]:
```
# Checking how many null values exists for each attribute
portfolio.isnull().sum() # -- There are no rows to be removed
```

Out[9]:
```
channels      0
difficulty    0
duration      0
offer_id      0
offer_type    0
reward        0
dtype: int64
```

In [10]:
```
#Inspect profile dataset
print(profile.shape)
profile.info()
profile.head()
```

```
(17000, 5)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17000 entries, 0 to 16999
Data columns (total 5 columns):
age                 17000 non-null int64
became_member_on    17000 non-null int64
gender              14825 non-null object
customer_id         17000 non-null object
income              14825 non-null float64
dtypes: float64(1), int64(2), object(2)
memory usage: 664.1+ KB
```

Out[10]:

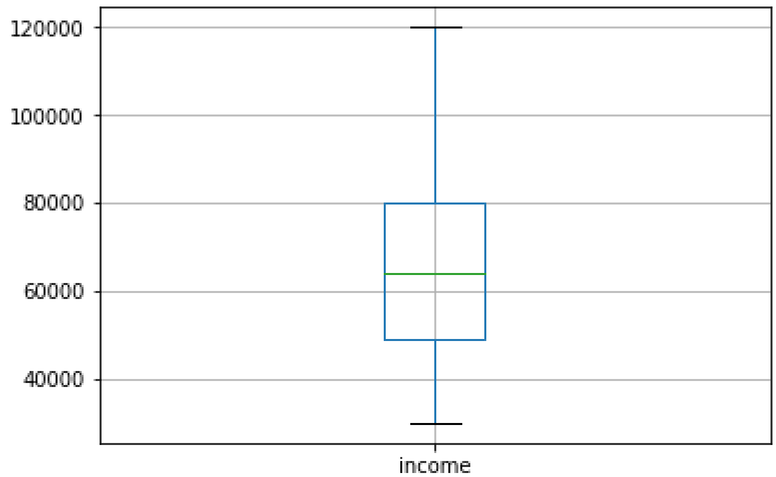
	age	became_member_on	gender	customer_id	income
0	118	20170212	None	68be06ca386d4c31939f3a4f0e3dd783	NaN
1	55	20170715	F	0610b486422d4921ae7d2bf64640c50b	112000.0
2	118	20180712	None	38fe809add3b4fcf9315a9694bb96ff5	NaN
3	75	20170509	F	78afa995795e4d85b5d9ceeca43f5fef	100000.0
4	118	20170804	None	a03223e636434f42ac4c3df47e8bac43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

In [11]:
```
# Check how many null values exists for each attribute
profile.isnull().sum()
```

Out[11]:
```
age                    0
became_member_on       0
gender              2175
customer_id            0
income              2175
dtype: int64
```

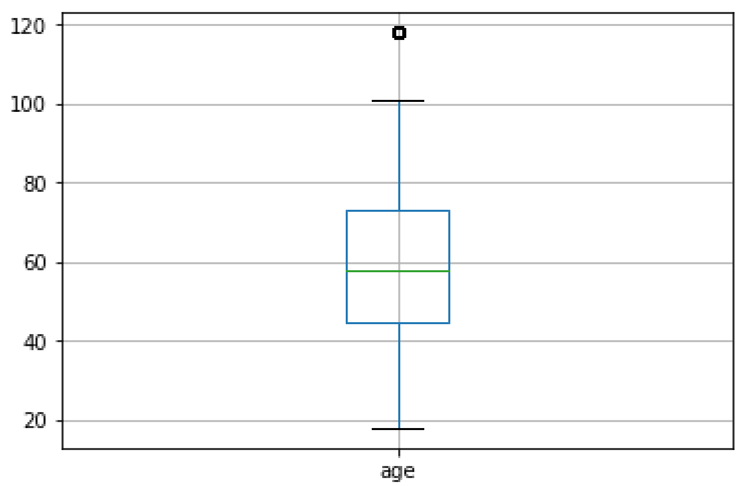
In [12]:
```
profile.boxplot(column=['income'], grid=True)
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7faa2b5fa860>



In [13]:
```
profile.boxplot(column=['age'], grid=True)
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7faa2b6247b8>



It seems we have an outlier for age closer to 120 value. On a deeper looker it seems outlier exists at age=118

In [14]:
```
# It seems there are 2175 rows having missing values for age and gender
# { age : 118, gender : None , income = 'NaN'}.
# Moreover, age =118 , although possible but does not seems right for a coffee di
len(profile[(profile.age == 118) & (profile.gender.isnull()) & (profile.income.i
```

Out[14]: 2175

In [15]:
```
# Dropping all columns whose all values are missing.
# profile.dropna(axis = 'rows', how='any', inplace=True)
condition = profile[(profile.age == 118) & (profile.gender.isnull()) & (profile.i
profile.drop(condition.index, inplace=True)
profile.shape
```

Out[15]: (14825, 5)

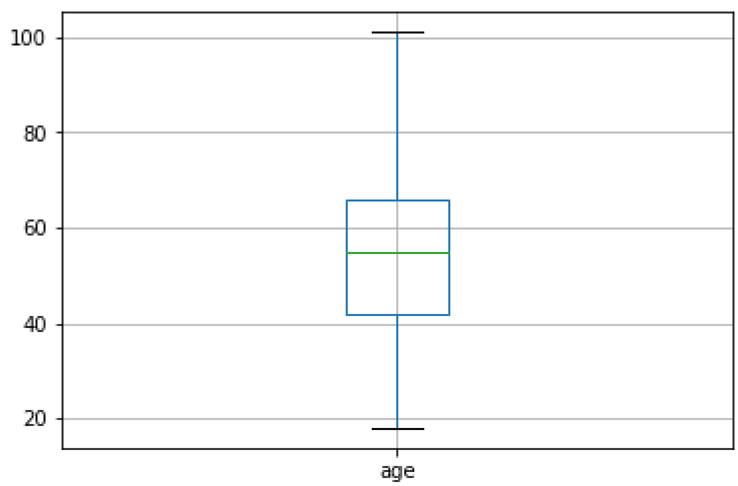
In [16]:
```
profile.isnull().sum()
profile.head()
```

Out[16]:

	age	became_member_on	gender	customer_id	income
1	55	20170715	F	0610b486422d4921ae7d2bf64640c50b	112000.0
3	75	20170509	F	78afa995795e4d85b5d9ceeca43f5fef	100000.0
5	68	20180426	M	e2127556f4f64592b11af22de27a7932	70000.0
8	65	20180209	M	389bc3fa690240e798340f5a15918d5c	53000.0
12	58	20171111	M	2eeac8d8feae4a8cad5a6af0499a211d	51000.0

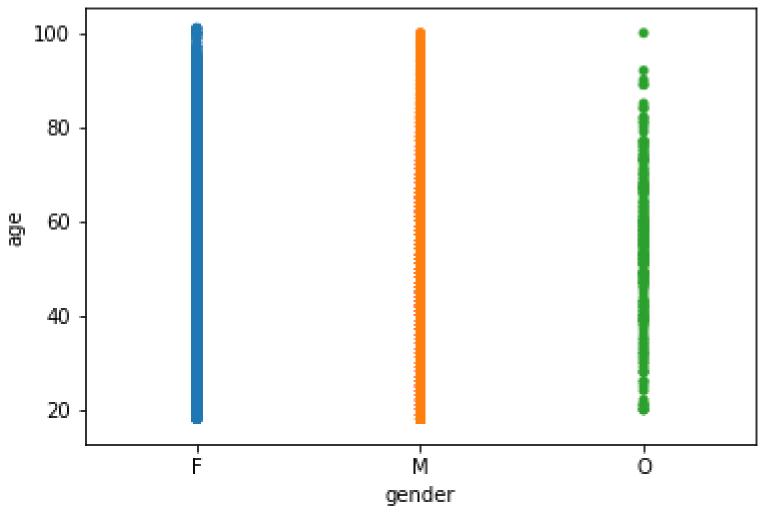
In [17]:
```
#Lets plot again to see if outlier has been removed.
profile.boxplot(column=['age'], grid=True)
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7faa2b5d3cc0>



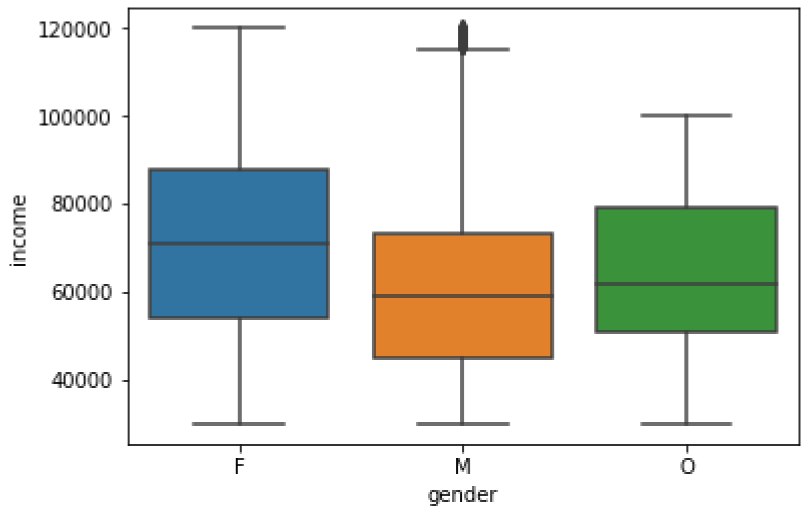
In [18]:
```
#Visualizing the gender distribution in a seaborn count plot
sns.stripplot(x="gender", y="age", data=profile)
# The plot below shows quite even distribution agewise for each gender.
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7faa2b581278>

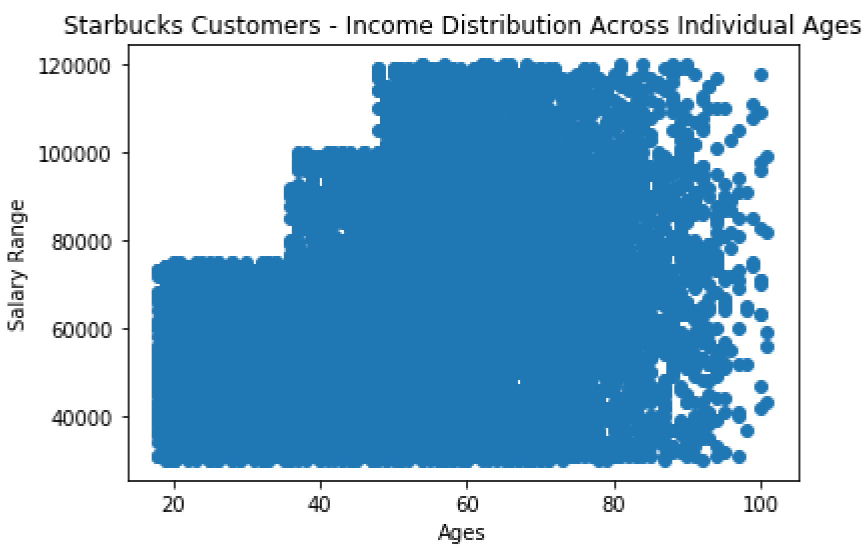


In [19]:
```
sns.boxplot(x="gender", y="income", data=profile)
#The plot below for male and others mean income is much less than female.
#This meant, female starbucks customers have more higher income than males, other
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7faa2b59d940>



In [20]:
```
#Visualizing the data in a scatter plot using individual ages instead of age rang
plt.scatter(data = profile, x = 'age', y = 'income')
plt.title('Starbucks Customers - Income Distribution Across Individual Ages');
plt.xlabel('Ages');
plt.ylabel('Salary Range');
plt.style.use('seaborn');
```



In [21]:
```
#Inspect transcript dataset
print(transcript.shape)
transcript.info()
transcript.head()
```

```
(306534, 4)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 306534 entries, 0 to 306533
Data columns (total 4 columns):
event     306534 non-null object
person    306534 non-null object
time      306534 non-null int64
value     306534 non-null object
dtypes: int64(1), object(3)
memory usage: 9.4+ MB
```

Out[21]:

	event	person	time	value
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	0	{'offer id': '9b98b8c7a33c4b65b9aebfe6a799e6d9'}
1	offer received	a03223e636434f42ac4c3df47e8bac43	0	{'offer id': '0b1e1539f2cc45b7b9fa7c272da2e1d7'}
2	offer received	e2127556f4f64592b11af22de27a7932	0	{'offer id': '2906b810c7d4411798c6938adc9daaa5'}
3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	0	{'offer id': 'fafdcd668e3743c1bb461111dcafc2a4'}
4	offer received	68617ca6246f4fbc85e91a2a49552598	0	{'offer id': '4d5c57ea9a6940dd891ad53e9dbe8da0'}

In [22]:
```
#Check count of various event
transcript["event"].value_counts(normalize=True)
```

Out[22]:
```
transaction        0.453304
offer received     0.248837
offer viewed       0.188315
offer completed    0.109544
Name: event, dtype: float64
```

In [23]:
```
# Checking how many null values exists for each attribute
transcript.isnull().sum()
```

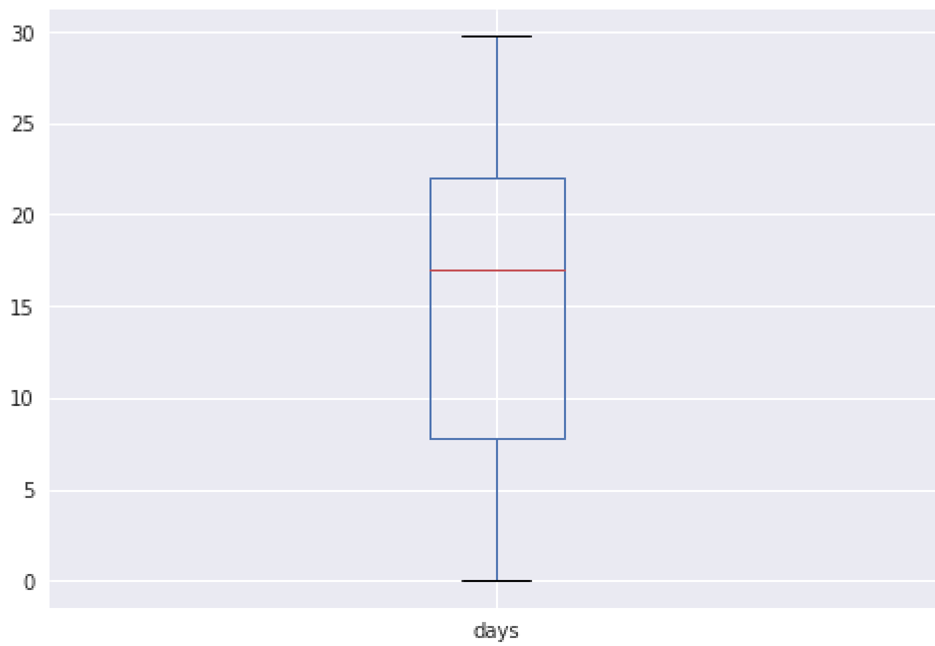
Out[23]:
```
event     0
person    0
time      0
value     0
dtype: int64
```

In [24]:
```
#Change 'time' column to 'days' along with the appropriate values
transcript['days'] = transcript['time'] / 24
transcript.drop(columns = ['time'], inplace = True)
transcript.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 306534 entries, 0 to 306533
Data columns (total 4 columns):
event     306534 non-null object
person    306534 non-null object
value     306534 non-null object
days      306534 non-null float64
dtypes: float64(1), object(3)
memory usage: 9.4+ MB
```

In [25]:
```
transcript.boxplot()
```

Out[25]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7faa2b4b14e0>
```



Algorithms and Techniques

For the benchmark, purpose I will be using very simple sklearn.svm.SVC (Support Vector Classification) with default parameters. For the relatively small dataset, this algorithm is well suited for classification tasks. A Support Vector Machine (SVM) is a powerful and versatile Machine Learning model, capable of performing linear or nonlinear classification, regression, and even outlier detection.

For the main model, I will experiment with "LinearLinear " and "Feed Forward Neural Network with 1 hidden layer".

With LinearLinear you can simultaneously explore different training objectives and choose the best solution from a validation set. In our case, I can optimize model for F1 measure, precision, recall, or accuracy.

The implementation requires below 3 steps:

- Preprocess : Normalization, or feature scaling, is an important preprocessing step for certain loss functions that ensures the model being trained on a dataset does not become dominated by the weight of a single feature. The Amazon SageMaker Linear Learner algorithm has a normalization option to assist with this preprocessing step. If normalization is turned on, the algorithm first goes over a small sample of the data to learn the mean value and standard deviation for each feature and for the label. Each of the features in the full dataset is then shifted to have mean of zero and scaled to have a unit standard deviation. Only the features can be normalized for binary classification and this is the default behavior.

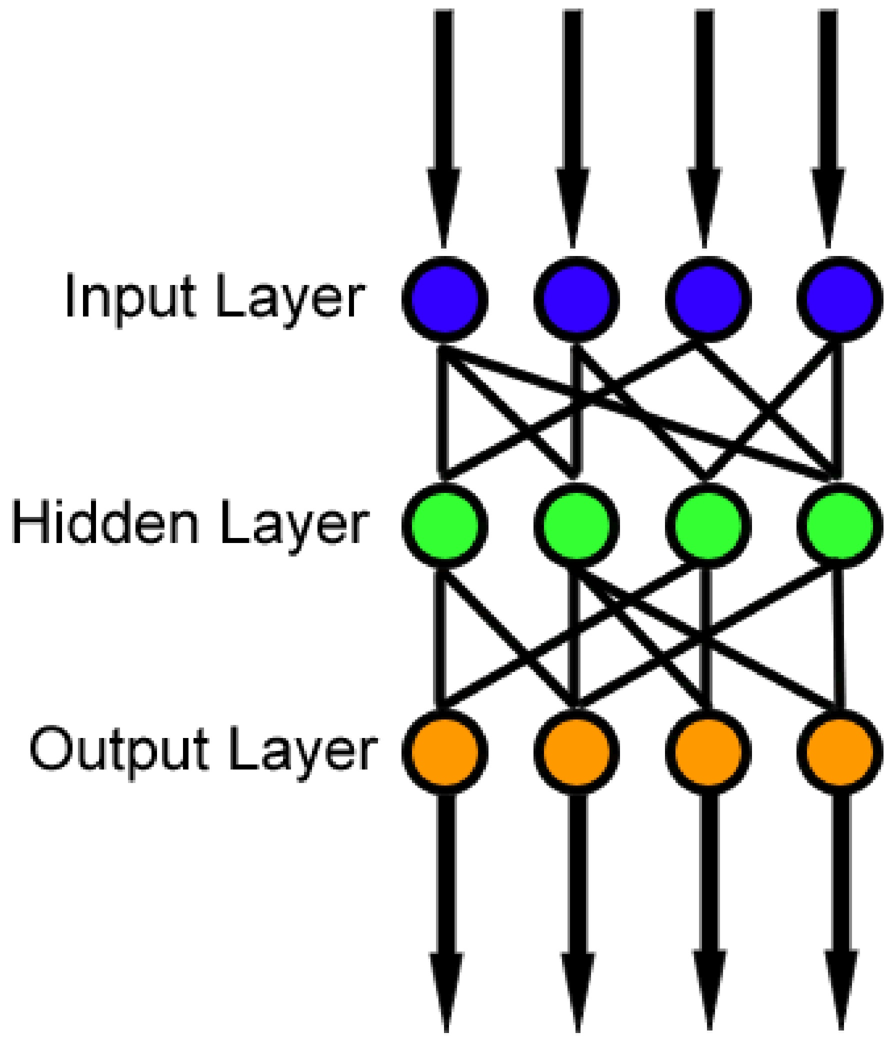
I will be performing this pre-processing step seperating and will not be using normalization feature of the model, so that I can keep the input consistent across model for measuring performances between them.

- Train : With the linear learner algorithm, you train with a distributed implementation of stochastic gradient descent (SGD). You can control the optimization process by choosing the optimization algorithm. For example, you can choose to use Adam, AdaGrad, stochastic gradient descent, or other optimization algorithms. You also specify their hyperparameters, such as momentum, learning rate, and the learning rate schedule. If you aren't sure which algorithm or hyperparameter value to use, choose a default that works for the majority of datasets.

I will be using SGD as an optimizer due to relatively small data set as it converges better, however takes longer training time Also I will use binary_classifier_model_selection_criteria='recall_at_target_precision', to gethighest recall at a given precision target, with target_precision of 90%

- Validate : For classification, a sample of the validation set is used to calibrate the classification threshold. The most optimal model selected is the one that achieves the best binary classification selection criteria on the validation set. Examples of such criteria include the F1 measure, accuracy, and cross-entropy loss.

With "Feed Forward Neural Network" the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output notes, with no cycles or loops in the network.



I will be using 1 hidden layer with hidden dimension will be calculated based on input feature set as below :

Reference : https://www.heatonresearch.com/2017/06/01/hidden-layers.html (https://www.heatonresearch.com/2017/06/01/hidden-layers.html)

- The number of hidden neurons should be between the size of the input layer and the size of the output layer.
- The number of hidden neurons should be 2/3 the size of the input layer, plus the size of the output layer.
- The number of hidden neurons should be less than twice the size of the input layer.

I will be setting dropout to 0.3 for regularization and preventing the co-adaptation of neurons. Reference : https://arxiv.org/abs/1207.0580 (https://arxiv.org/abs/1207.0580)

Since we need binary classification (0 or 1), we will be using sigmoid function for the output layer. Reference: https://medium.com/analytics-vidhya/sigmoid-function-with-pytorch-99cb2209ad89 (https://medium.com/analytics-vidhya/sigmoid-function-with-pytorch-99cb2209ad89)

For training and optmization, we will be using Adam optmizer as it ombines the best properties of RMSProp and AdaGrad to work well even with noisy or sparse datasets Reference : https://towardsdatascience.com/learning-parameters-part-5-65a2f3583f7d (https://towardsdatascience.com/learning-parameters-part-5-65a2f3583f7d)

and Since we have a sigmoid function as output, we will use BCELoss as loss function Reference : https://towardsdatascience.com/adam-latest-trends-in-deep-learning-optimization-6be9a291375c (https://towardsdatascience.com/adam-latest-trends-in-deep-learning-optimization-6be9a291375c) https://medium.com/analytics-vidhya/simple-neural-network-with-bceloss-for-binary-classification-for-a-custom-dataset-8d5c69ffffee (https://medium.com/analytics-vidhya/simple-neural-network-with-bceloss-for-binary-classification-for-a-custom-dataset-8d5c69ffffee)

Data will be cleansed, pre-processing, feature engineered and normalized before feeding into vairous model described above.

Benchmark

In this project, I will aim for **higher precision** (lower False positives) vs recall (lower false negatives) alongwith higher F1 score, as it is ok to send offer which is less relevant to the customer rather than not sending at all

```
* True positive  = offer used and model classifies them correctly
* False positive = offer not used , however model classifies them incorr
ectly (offer used)
* False negative = offer used , however model classifies them incorrectl
y (offer not used)
* True negative  = offer not used and model classifies them correctly
```

		Actual	
		Positive	Negative
Predicted	Positive	True Positive	False Positive
	Negative	False Negative	True Negative

Since we do not have any past data/result, I will baseline my metric based on benchmark model - SVC and then will select LinearLeaner or Feed forward nueral network, based on how they perform against the benchmark metric - higher precision

III. Methodology

Data Preprocessing

Reference :

- https://elitedatascience.com/wp-content/uploads/2018/05/Feature-Engineering-Checklist.pdf (https://elitedatascience.com/wp-content/uploads/2018/05/Feature-Engineering-Checklist.pdf)
- https://towardsdatascience.com/why-automated-feature-engineering-will-change-the-way-you-do-machine-learning-5c15bf188b96 (https://towardsdatascience.com/why-automated-feature-engineering-will-change-the-way-you-do-machine-learning-5c15bf188b96)

Kindly refer code comments for pre-processing steps below:

In [26]:

```
#This helper function extracts attribute value from a column containing json str
def json_attr_extract(x, attr):
    x  = str(x).replace("'", '"') # This is required, as json expects double quo
    x  = x.replace('offer id', 'offer_id') # Replacing offer id with offer_id
    x  = json.loads(x)
    if attr in x:
        val = x[attr]
    else:
        val = None # for some of records, reward attribute does not exists
    return val
```

In [27]:

```
#Create seperate transaction dataframe based on event
transcript_transaction = transcript[transcript.event == 'transaction'].copy()
#transcript_offer = transcript[transcript.event != 'transaction']
transcript_transaction['amount'] = transcript.value.apply(json_attr_extract, attr
transcript_transaction.drop(columns =["value"], axis=1, inplace = True)
transcript_transaction.head()
```

Out[27]:

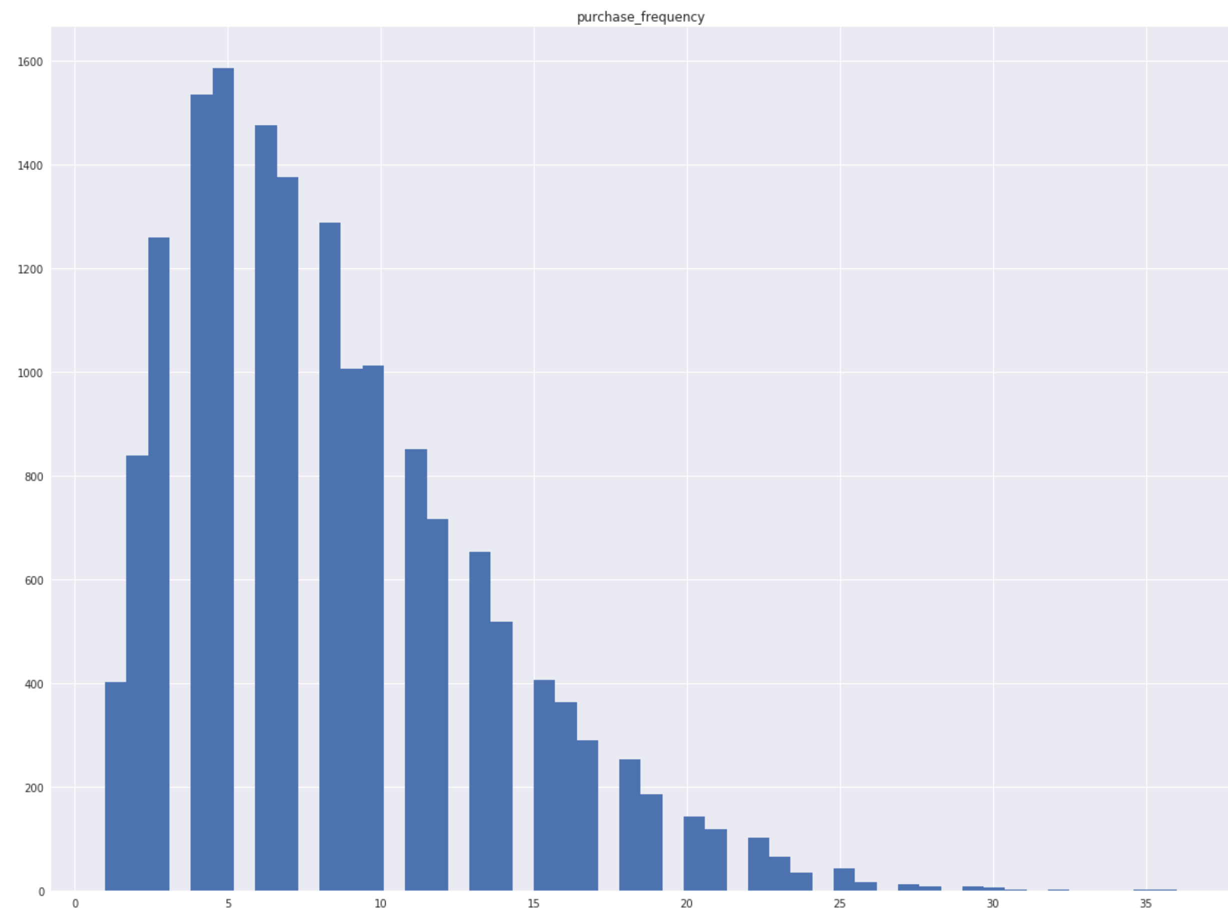
	event	person	days	amount
12654	transaction	02c083884c7d45b39cc68e1314fec56c	0.0	0.83
12657	transaction	9fa9ae8f57894cc9a3b8a9bbe0fc1b2f	0.0	34.56
12659	transaction	54890f68699049c2a04d415abc25e717	0.0	13.23
12670	transaction	b2f1cd155b864803ad8334cdf13c4bd2	0.0	19.51
12671	transaction	fe97aa22dd3e48c8b143116a8403dd52	0.0	18.97

In [28]:
```
# Creating new data set from transaction to extract frequency of transactions at
# This could be interesting feature which shows how much customer is interested.
# This will help to identify everyday user vs irregular user
purchase_frequency = transcript_transaction.groupby(["person"]).count()
purchase_frequency.rename(columns = {'days' : 'purchase_frequency' }, inplace =
purchase_frequency.drop(columns =["amount", "event"], axis=1, inplace = True)
purchase_frequency.head()
```

Out[28]:

	purchase_frequency
person	
0009655768c64bdeb2e877511632db8f	8
00116118485d4dfda04fdbaba9a87b5c	3
0011e0d4e6b944f998e987f904e8c1e5	5
0020c2b971eb4e9188eac86d93036a77	8
0020ccbbb6d84e358d3414a3ff76cffd	12

In [29]:
```
purchase_frequency.hist(bins=50, figsize=(20,15))
plt.show()
```



In [30]:
```
purchase_frequency.describe()
purchase_frequency.shape
```

Out[30]: (16578, 1)

In [31]:
```
#Separating and one hot encoding the channels field
# Reference : https://scikit-learn.org/stable/modules/generated/sklearn.preproce

#Initializing our MultiLabelBinarizer object
channels_one_hot = MultiLabelBinarizer()
#One hot encoding the data
sep_channels = channels_one_hot.fit_transform(portfolio['channels'])
#Building a DataFrame around these channels
channels_df = pd.DataFrame(data = sep_channels, columns = channels_one_hot.class
#Concatenating the new columns to our primary 'portfolio' DataFrame
portfolio = pd.concat([portfolio, channels_df], axis = 1)
#Changing the column names to affix 'channels_' prefix
portfolio.rename(columns = {'email': 'channel_email', 'mobile': 'channel_mobile'
#Viewing our changes
portfolio.head()
```

Out[31]:

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

In [32]:
```
# Define new features based on value column in transcript data set
transcript['offer_id'] = transcript.value.apply(json_attr_extract, attr ='offer_
#transcript['reward'] = transcript.value.apply(json_attr_extract, attr ='reward',
transcript['amount'] = transcript.value.apply(json_attr_extract,attr ='amount')
```

In [33]:
```
# No longer require value column
transcript.drop(columns =["value"], axis=1, inplace = True)
transcript.drop(columns =["days"], axis=1, inplace = True)
```

In [34]:
```
#Inspect transcript dataset
print(transcript.shape)
transcript.info()
transcript.head()
```

```
(306534, 4)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 306534 entries, 0 to 306533
Data columns (total 4 columns):
event       306534 non-null object
person      306534 non-null object
offer_id    167581 non-null object
amount      138953 non-null float64
dtypes: float64(1), object(3)
memory usage: 9.4+ MB
```

Out[34]:

	event	person	offer_id	amount
0	offer received	78afa995795e4d85b5d9ceeca43f5fef	9b98b8c7a33c4b65b9aebfe6a799e6d9	NaN
1	offer received	a03223e636434f42ac4c3df47e8bac43	0b1e1539f2cc45b7b9fa7c272da2e1d7	NaN
2	offer received	e2127556f4f64592b11af22de27a7932	2906b810c7d4411798c6938adc9daaa5	NaN
3	offer received	8ec6ce2a7e7949b1bf142def7d0e0586	fafdcd668e3743c1bb461111dcafc2a4	NaN
4	offer received	68617ca6246f4fbc85e91a2a49552598	4d5c57ea9a6940dd891ad53e9dbe8da0	NaN

In [35]:
```
#Changing 'became_member_on' column to a date type
profile['became_member_on'] = profile['became_member_on'].apply(lambda x: dateti
profile['became_member_on'].describe()
```

Out[35]:
```
count          14825
unique          1707
top       2017-08-19
freq              39
Name: became_member_on, dtype: object
```

In [36]:
```
#Using one hot encoding to convert gender, and offer_type
from sklearn.preprocessing import OneHotEncoder
gender_encoder = OneHotEncoder()

# This is important as we removed some rows earlier from dataset,few indexes will
#This will ensure , when we concat we do not run into index mismatch issue causi
profile.reset_index(drop=True, inplace= True)

gender_sep = gender_encoder.fit_transform(profile[['gender']])
column_names = [ x.replace('x0_', 'gender_') for x  in gender_encoder.get_featur
#Building a DataFrame around these genders
gender_df = pd.DataFrame(data = gender_sep.toarray(), columns = column_names)

profile = pd.concat([profile, gender_df], axis = 1)
#profile.concat(gender_df, axis = 1, inplace = True)

#Validate profile data after gender hot-1-encoding
print(len(profile[(profile.gender == 'F') & ( (profile.gender_O == 1.0) | (profi
print(len(profile[(profile.gender == 'M') & ( (profile.gender_O == 1.0) | (profi
print(len(profile[(profile.gender == 'O') & ( (profile.gender_M == 1.0) | (profi

#Dropping original column
profile.drop(columns = ['gender'], inplace = True)
profile.head()
```

```
0
0
0
```

Out[36]:

	age	became_member_on	customer_id	income	gender_F	gender_M	g
0	55	2017-07-15	0610b486422d4921ae7d2bf64640c50b	112000.0	1.0	0.0	
1	75	2017-05-09	78afa995795e4d85b5d9ceeca43f5fef	100000.0	1.0	0.0	
2	68	2018-04-26	e2127556f4f64592b11af22de27a7932	70000.0	0.0	1.0	
3	65	2018-02-09	389bc3fa690240e798340f5a15918d5c	53000.0	0.0	1.0	
4	58	2017-11-11	2eeac8d8feae4a8cad5a6af0499a211d	51000.0	0.0	1.0	

In [37]:
```
#Calculating number of days as a member ending on 2017-01-01 in new column 'membe
#Reference : https://stackoverflow.com/questions/26072087/pandas-number-of-days-e

# End date is defined with assumption that new data will always have become_membe
end_date = pd.Timestamp('2017-01-01')
end_date = pd.to_datetime(end_date)
profile['member_days'] = np.abs((pd.to_datetime(profile['became_member_on']) - en

#Inspect
profile.head(10)
```

Out[37]:

	age	became_member_on	customer_id	income	gender_F	gender_M	g
0	55	2017-07-15	0610b486422d4921ae7d2bf64640c50b	112000.0	1.0	0.0	
1	75	2017-05-09	78afa995795e4d85b5d9ceeca43f5fef	100000.0	1.0	0.0	
2	68	2018-04-26	e2127556f4f64592b11af22de27a7932	70000.0	0.0	1.0	
3	65	2018-02-09	389bc3fa690240e798340f5a15918d5c	53000.0	0.0	1.0	
4	58	2017-11-11	2eeac8d8feae4a8cad5a6af0499a211d	51000.0	0.0	1.0	
5	61	2017-09-11	aa4862eba776480b8bb9c68455b8c2e1	57000.0	1.0	0.0	
6	26	2014-02-13	e12aeaf2d47d42479ea1c4ac3d8286c6	46000.0	0.0	1.0	
7	62	2016-02-11	31dda685af34476cad5bc968bdb01c53	71000.0	1.0	0.0	
8	49	2014-11-13	62cf5e10845442329191fc246e7bcea3	52000.0	0.0	1.0	
9	57	2017-12-31	6445de3b47274c759400cd68131d91b4	42000.0	0.0	1.0	

In [38]:
```
#Using one hot encoding to convert gender, and offer_type - as there are categor
from sklearn.preprocessing import OneHotEncoder
offer_encoder = OneHotEncoder()

# This is important as we removed some rows earlier from dataset,few indexes wil
#This will ensure , when we concat we do not run into index mismatch issue causi
portfolio.reset_index(drop = True, inplace= True)

offer_sep = offer_encoder.fit_transform(portfolio[['offer_type']])
column_names = [ x.replace('x0_', 'offer_type_') for x  in offer_encoder.get_fea
#Building a DataFrame around these genders
offer_df = pd.DataFrame(data = offer_sep.toarray(), columns = column_names)

portfolio = pd.concat([portfolio, offer_df], axis = 1)


#Validate profile data after offer_type hot-1-encoding
print(len(portfolio[(portfolio.offer_type == 'informational') & ( (portfolio.off
print(len(portfolio[(portfolio.offer_type == 'bogo') & ( (portfolio.offer_type_d
print(len(portfolio[(portfolio.offer_type == 'discount') & ( (portfolio.offer_ty

#Dropping original column
portfolio.drop(columns = ['offer_type'], inplace = True)
portfolio.head()
```

```
0
0
0
```

Out[38]:

	channels	difficulty	duration	offer_id	reward	channel_email	chann
0	[email, mobile, social]	10	7	ae264e3637204a6fb9bb56bc8210ddfd	10	1	
1	[web, email, mobile, social]	10	5	4d5c57ea9a6940dd891ad53e9dbe8da0	10	1	
2	[web, email, mobile]	0	4	3f207df678b143eea3cee63160fa8bed	0	1	
3	[web, email, mobile]	5	7	9b98b8c7a33c4b65b9aebfe6a799e6d9	5	1	
4	[web, email]	20	10	0b1e1539f2cc45b7b9fa7c272da2e1d7	5	1	

In [39]:
```
#This function returns where the person viewed a specific offer by checking in sp
def is_offer_viewed(person_id, offer_id, offers_df):
    offers_df = offers_df[(offers_df['person'] == person_id) & (offers_df['offer_
    return int(not offers_df.empty)
```

In [40]:
```
transcript["event"].value_counts()
#Create seperate data set for completed offers
completed_offers = transcript[transcript.event == 'offer completed'].copy()
#Create seperate data set for viewed offers
viewed_offers = transcript[transcript.event == 'offer viewed'].copy()
#Create new feature "offer_used", which defines whether customer has completed tl
# In other words, he was influenced by the offer. This is the data we are intere:
completed_offers["offer_used"] = completed_offers.apply(lambda row : is_offer_vi
```

In [41]:
```
#Inspect completed_offers dataset
print(completed_offers.shape)
completed_offers.info()
completed_offers.head()
```

```
(33579, 5)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 33579 entries, 12658 to 306527
Data columns (total 5 columns):
event         33579 non-null object
person        33579 non-null object
offer_id      33579 non-null object
amount        0 non-null float64
offer_used    33579 non-null int64
dtypes: float64(1), int64(1), object(3)
memory usage: 1.5+ MB
```

Out[41]:

	event	person	offer_id	amount
12658	offer completed	9fa9ae8f57894cc9a3b8a9bbe0fc1b2f	2906b810c7d4411798c6938adc9daaa5	NaN
12672	offer completed	fe97aa22dd3e48c8b143116a8403dd52	fafdcd668e3743c1bb461111dcafc2a4	NaN
12679	offer completed	629fc02d56414d91bca360decdfa9288	9b98b8c7a33c4b65b9aebfe6a799e6d9	NaN
12692	offer completed	676506bad68e4161b9bbaffeb039626b	ae264e3637204a6fb9bb56bc8210ddfd	NaN
12697	offer completed	8f7dd3b2afe14c078eb4f6e6fe4ba97d	4d5c57ea9a6940dd891ad53e9dbe8da0	NaN

In [42]:
```
# Time to create Final Data set...
# Join completed_offers with profile data set. Using inner join as there are pers
# in profile data set and vice versa.
result = completed_offers.merge(profile, how="inner", left_on="person" , right_o
#Join resultant set with portfolio data set.
offers_completed_final = result.merge(portfolio, how="inner", left_on="offer_id",
```

In [43]:
```
#Shape check --Before
offers_completed_final.shape
#Using left join, as some transactions might be missing for person, we may have t
final_dataset = offers_completed_final.merge(purchase_frequency, how="left", left
#Shape check --After
final_dataset.shape
```

Out[43]: (32444, 25)

In [44]:
```
#Dropping not required columns
#offer_type_informational is not useful as there will not be any transaction - co
final_dataset.drop(columns =["event", "channels", "amount", "person","became_memb
```

In [45]:
```
final_dataset["channel_email"].value_counts()
#It seems channel_email does not provide any constant value as 1 , and thus can b
#Reduces Overfitting: Less redundant data means less opportunity to make decision
final_dataset.drop(columns =["channel_email"], axis=1, inplace = True)
```

In [46]:
```
# Since same person can buy same offers over multiple periods, we need to remove
# Note : These duplicate rows will same all attributes as same value
final_dataset.drop_duplicates(inplace = True)
```

In [47]:
```
#Inspect final data set.
print(len(final_dataset.columns),final_dataset.columns )
print(final_dataset.shape)
final_dataset.info()
```

```
16 Index(['offer_used', 'age', 'income', 'gender_F', 'gender_M', 'gender_O',
       'member_days', 'difficulty', 'duration', 'reward', 'channel_mobile',
       'channel_social', 'channel_web', 'offer_type_bogo',
       'offer_type_discount', 'purchase_frequency'],
      dtype='object')
(27941, 16)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 27941 entries, 0 to 32443
Data columns (total 16 columns):
offer_used             27941 non-null int64
age                    27941 non-null int64
income                 27941 non-null float64
gender_F               27941 non-null float64
gender_M               27941 non-null float64
gender_O               27941 non-null float64
member_days            27941 non-null int64
difficulty             27941 non-null int64
duration               27941 non-null int64
reward                 27941 non-null int64
channel_mobile         27941 non-null int64
channel_social         27941 non-null int64
channel_web            27941 non-null int64
offer_type_bogo        27941 non-null float64
offer_type_discount    27941 non-null float64
purchase_frequency     27941 non-null int64
dtypes: float64(6), int64(10)
memory usage: 3.6 MB
```

In [48]:
```
final_dataset.isnull().sum()
```

Out[48]:
```
offer_used             0
age                    0
income                 0
gender_F               0
gender_M               0
gender_O               0
member_days            0
difficulty             0
duration               0
reward                 0
channel_mobile         0
channel_social         0
channel_web            0
offer_type_bogo        0
offer_type_discount    0
purchase_frequency     0
dtype: int64
```

In [49]:
```
final_dataset.head()
```

Out[49]:

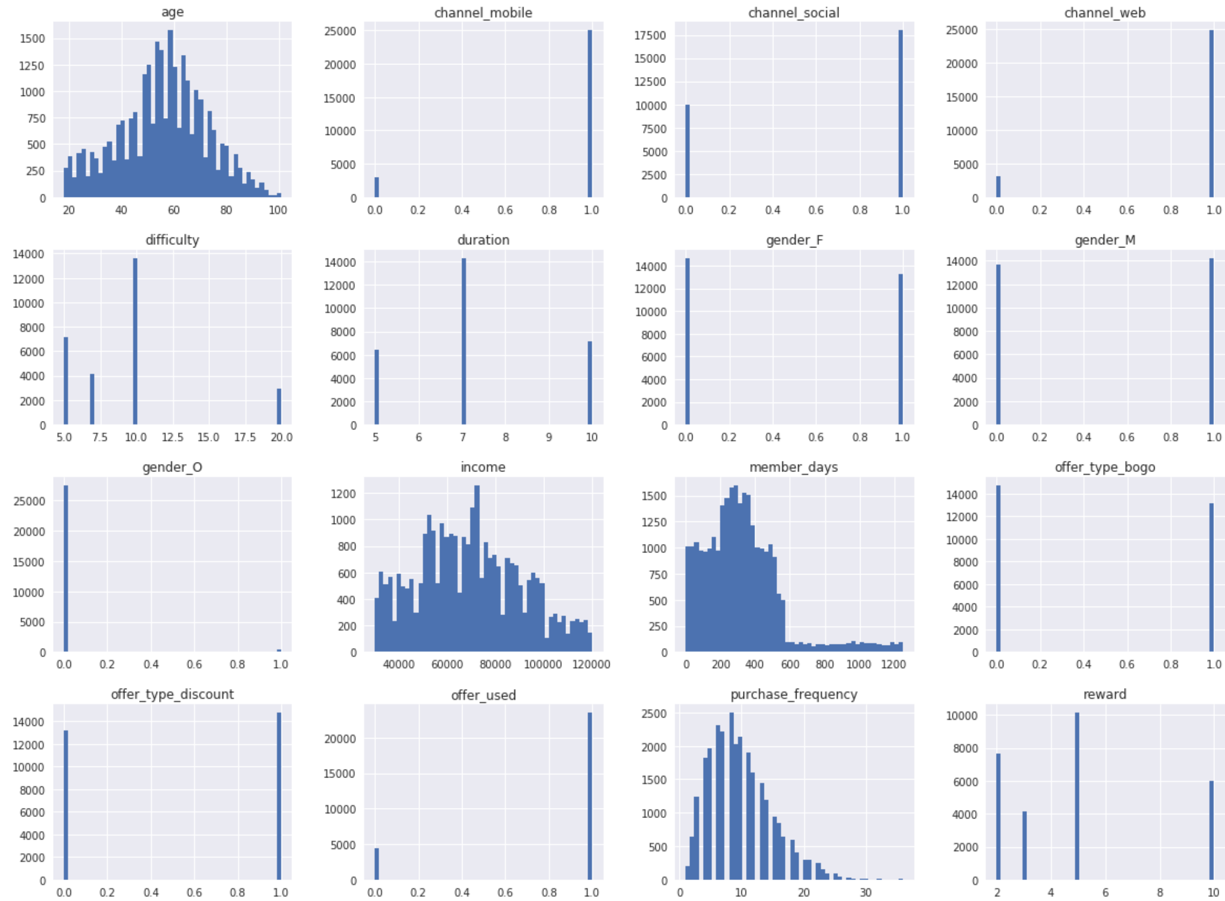
	offer_used	age	income	gender_F	gender_M	gender_O	member_days	difficulty	duration	re
0	1	42	96000.0	0.0	1.0	0.0	350	10	7	
1	1	52	72000.0	0.0	1.0	0.0	520	10	7	
2	1	67	67000.0	1.0	0.0	0.0	460	10	7	
3	0	54	39000.0	0.0	1.0	0.0	507	10	7	
4	0	64	83000.0	1.0	0.0	0.0	8	10	7	

In [50]:
```
final_dataset.describe()
```

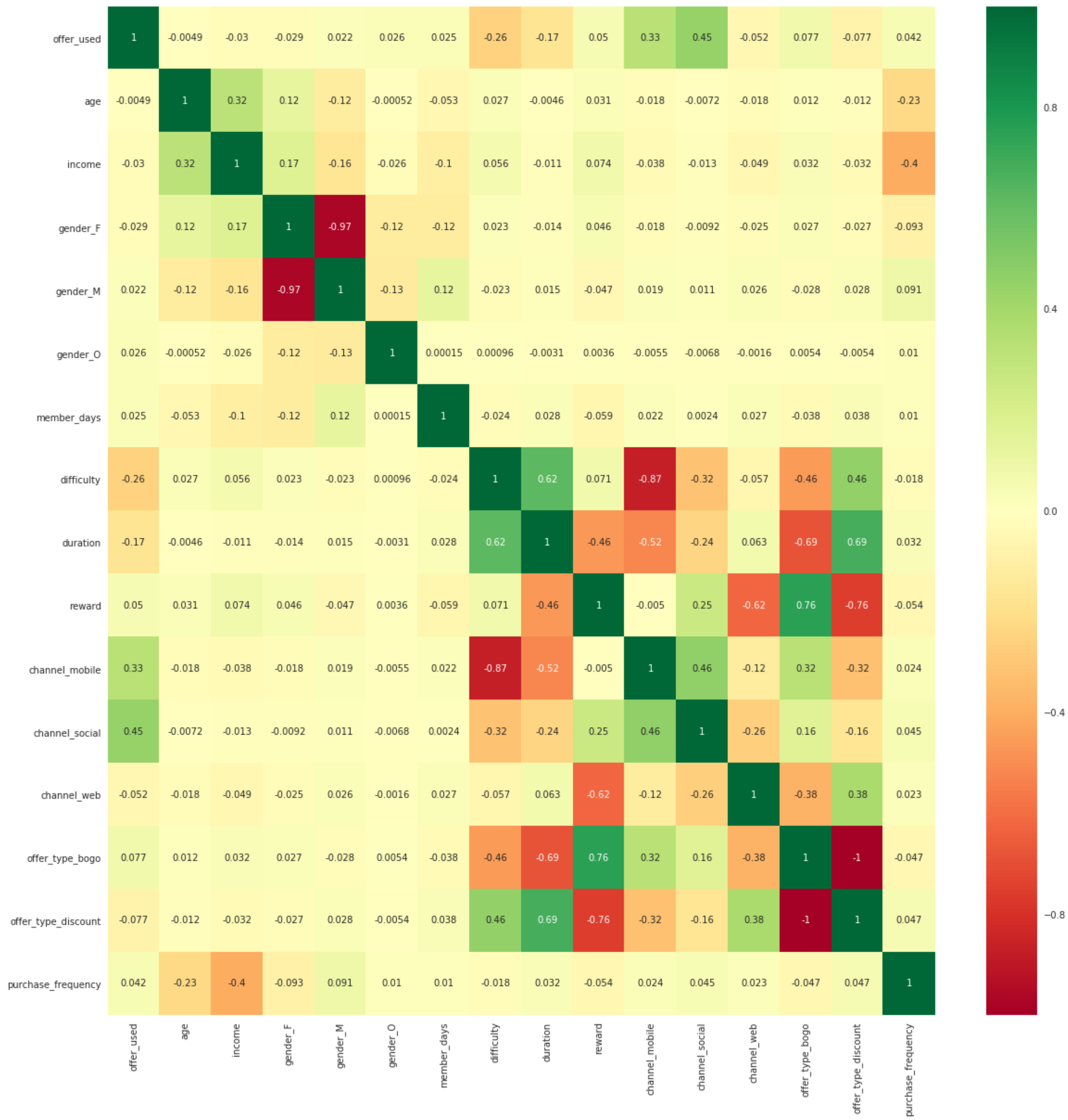
Out[50]:

	offer_used	age	income	gender_F	gender_M	gender_O	mem
count	27941.000000	27941.000000	27941.000000	27941.000000	27941.000000	27941.000000	2794
mean	0.841022	55.780824	69328.549443	0.474500	0.510146	0.015354	32
std	0.365662	16.831182	21602.962094	0.499358	0.499906	0.122958	22
min	0.000000	18.000000	30000.000000	0.000000	0.000000	0.000000	
25%	1.000000	45.000000	53000.000000	0.000000	0.000000	0.000000	17
50%	1.000000	57.000000	68000.000000	0.000000	1.000000	0.000000	29
75%	1.000000	67.000000	85000.000000	1.000000	1.000000	0.000000	43
max	1.000000	101.000000	120000.000000	1.000000	1.000000	1.000000	125

In [51]:
```
final_dataset.hist(bins=50, figsize=(20,15))
plt.show()
```



In [52]:
```
#Reference : https://towardsdatascience.com/feature-selection-techniques-in-mach
#Correlation Matrix with Heatmap
start_index = 1
end_index = len(final_dataset.columns)
X = final_dataset.iloc[:,start_index:end_index]  #independent columns
y = final_dataset.iloc[:,0]   #target column
#get correlations of each features in dataset
corrmat = final_dataset.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(20,20))
#plot heat map
g=sns.heatmap(final_dataset[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```



In [53]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
#apply SelectKBest class to extract top 10 best features
bestfeatures = SelectKBest(score_func=chi2, k=10)
fit = bestfeatures.fit(X,y)
dfscores = pd.DataFrame(fit.scores_)
dfcolumns = pd.DataFrame(X.columns)
#concat two dataframes for better visualization
featureScores = pd.concat([dfcolumns,dfscores],axis=1)
featureScores.columns = ['Specs','Score']  #naming the dataframe columns
print(featureScores.nlargest(10,'Score'))  #print 10 best features
```

```
                 Specs          Score
1               income  173558.339953
6           difficulty    3515.446089
5          member_days    2812.098162
10      channel_social    1988.148881
7             duration     348.828630
9       channel_mobile     313.192101
14  purchase_frequency     129.420541
8               reward     119.005557
12      offer_type_bogo      88.184591
13  offer_type_discount      78.965918
```

In [54]:
```
# Hmm something is not right, the output of above two set does not match.
#SelectKBest is showing income as best feature but we did not find any correlati
# Similar behaviour is observed for difficulty, members days etc.
#This is due to  different scales for these feature set.
#Hence , we need to apply feature scaling
```

In [55]:
```
#Scaling the data
#https://towardsdatascience.com/scale-standardize-or-normalize-with-scikit-learn
#Using MinMaxScalar so that it has zero effects on 1-hot encoded features
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaled_dataset = scaler.fit_transform(final_dataset)

#Rebuilding the DataFrame
column_names = final_dataset.columns.values.tolist()
final_dataset_scaled = pd.DataFrame(scaled_dataset, columns = column_names)
final_dataset_scaled.head()
```

Out[55]:

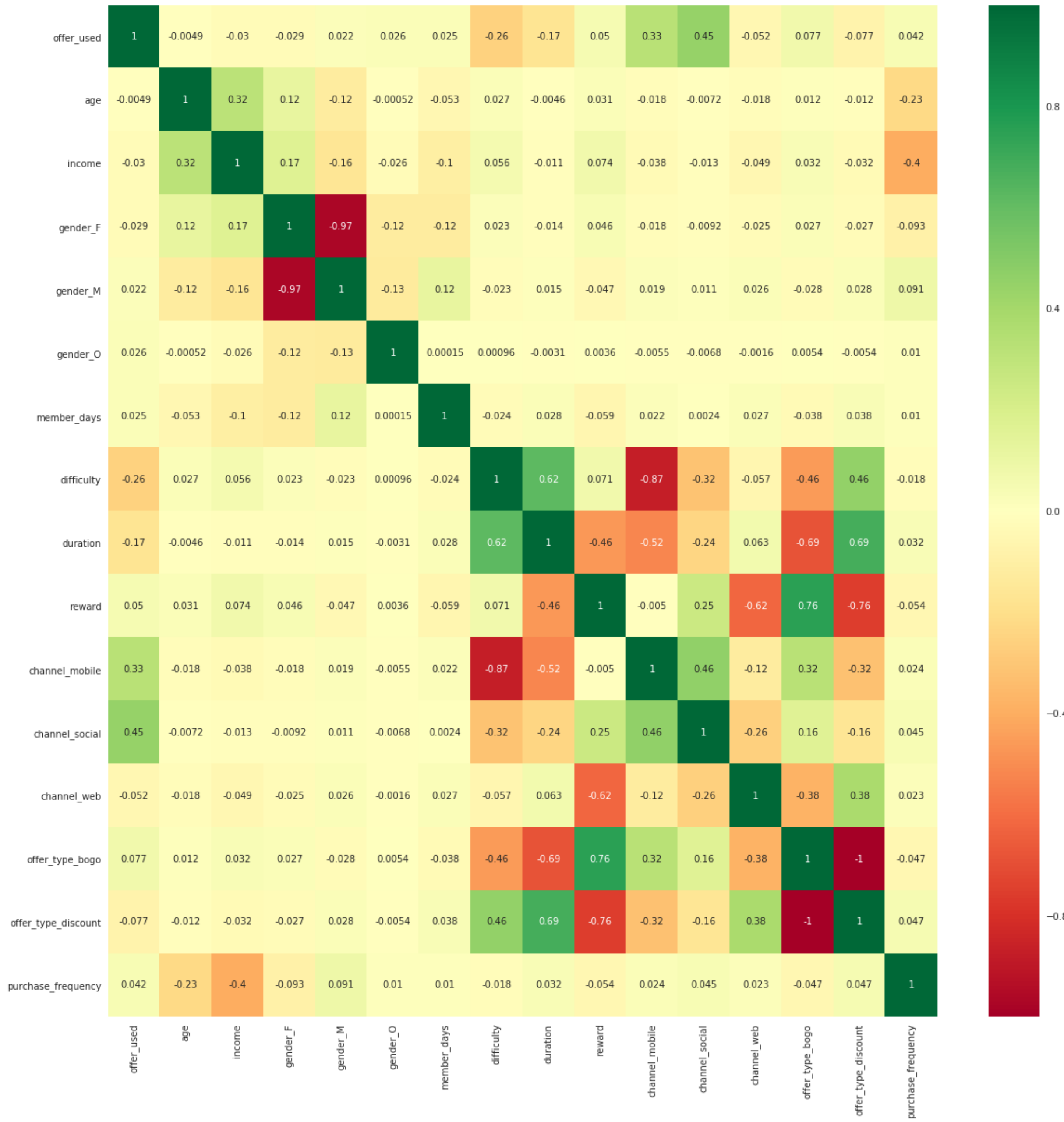
	offer_used	age	income	gender_F	gender_M	gender_O	member_days	difficulty	durati
0	1.0	0.289157	0.733333	0.0	1.0	0.0	0.279553	0.333333	(
1	1.0	0.409639	0.466667	0.0	1.0	0.0	0.415335	0.333333	(
2	1.0	0.590361	0.411111	1.0	0.0	0.0	0.367412	0.333333	(
3	0.0	0.433735	0.100000	0.0	1.0	0.0	0.404952	0.333333	(
4	0.0	0.554217	0.588889	1.0	0.0	0.0	0.006390	0.333333	(

In [56]:
```
#Validate - Reversal
inverse_dataset =  scaler.inverse_transform(scaled_dataset)
inversed_df = pd.DataFrame(inverse_dataset, columns = column_names)
inversed_df.head()
```

Out[56]:

	offer_used	age	income	gender_F	gender_M	gender_O	member_days	difficulty	duration	re
0	1.0	42.0	96000.0	0.0	1.0	0.0	350.0	10.0	7.0	
1	1.0	52.0	72000.0	0.0	1.0	0.0	520.0	10.0	7.0	
2	1.0	67.0	67000.0	1.0	0.0	0.0	460.0	10.0	7.0	
3	0.0	54.0	39000.0	0.0	1.0	0.0	507.0	10.0	7.0	
4	0.0	64.0	83000.0	1.0	0.0	0.0	8.0	10.0	7.0	

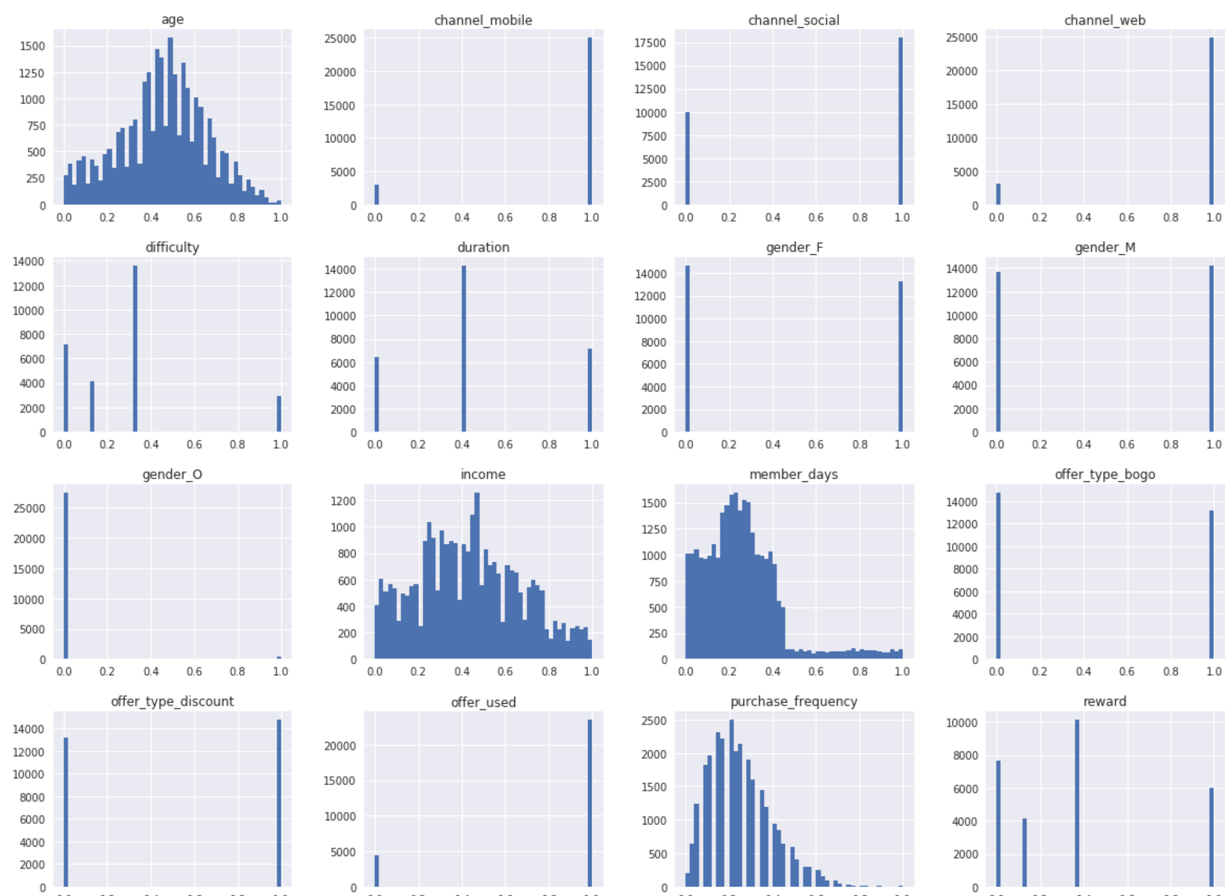
In [57]:
```
#Reference : https://towardsdatascience.com/feature-selection-techniques-in-mach
#Correlation Matrix with Heatmap
start_index = 1
end_index = len(final_dataset_scaled.columns)
X = final_dataset_scaled.iloc[:,start_index:end_index]  #independent columns
y = final_dataset_scaled.iloc[:,0]   #target column
#get correlations of each features in dataset
corrmat = final_dataset.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(20,20))
#plot heat map
g=sns.heatmap(final_dataset[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```



In [58]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
#apply SelectKBest class to extract top 10 best features
bestfeatures = SelectKBest(score_func=chi2, k=10)
fit = bestfeatures.fit(X,y)
dfscores = pd.DataFrame(fit.scores_)
dfcolumns = pd.DataFrame(X.columns)
#concat two dataframes for better visualization
featureScores = pd.concat([dfcolumns,dfscores],axis=1)
featureScores.columns = ['Specs','Score']  #naming the dataframe columns
print(featureScores.nlargest(10,'Score'))  #print 10 best features
```

```
                 Specs        Score
10      channel_social  1988.148881
6           difficulty   505.652859
9       channel_mobile   313.192101
7             duration   220.639872
12      offer_type_bogo   88.184591
13  offer_type_discount   78.965918
8               reward    24.933450
4             gender_O    18.078016
2             gender_F    12.069760
11         channel_web     8.427039
```

In [59]:
```
final_dataset_scaled.hist(bins=50, figsize=(20,15))
plt.show()
```



In [60]:
```
# Split data into labels and features
valid_offers_used = final_dataset_scaled['offer_used'].copy()
#It was identified age does not have much correlation with offer_used
#valid_offers_features = final_dataset_scaled.drop(['offer_used'], axis=1)
valid_offers_features = final_dataset_scaled.drop(['offer_used', 'age'], axis=1)
#valid_offers_features = final_dataset_scaled.drop(['offer_used','age', 'purchase
```

In [61]:
```
# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(valid_offers_features,
                                                    valid_offers_used,
                                                    test_size = 0.2,
                                                    random_state = 42)
```

In [62]:
```
#Validate 80/20 split based on offer used in train and test set.
print("20% of Offer_used = 0 : ", int(final_dataset_scaled.offer_used.value_coun
print( "Count of Offer used=0 in test set : ", y_test.value_counts()[0])
```

```
20% of Offer_used = 0 :  888
Count of Offer used=0 in test set :  900
```

In [63]:
```
y_train.value_counts(normalize=True)
```

Out[63]:
```
1.0    0.841535
0.0    0.158465
Name: offer_used, dtype: float64
```

In [64]:
```
y_test.value_counts(normalize=True)
```

Out[64]:
```
1.0    0.838969
0.0    0.161031
Name: offer_used, dtype: float64
```

In [65]:
```
#Upload Data to S3
# session and role
sagemaker_session = sagemaker.Session()
role = sagemaker.get_execution_role()

# create an S3 bucket
bucket = sagemaker_session.default_bucket()
```

In [66]:
```
def make_csv(x, y, filename, data_dir):
    '''Merges features and labels and converts them into one csv file with labels
       :param x: Data features
       :param y: Data labels
       :param file_name: Name of csv file, ex. 'train.csv'
       :param data_dir: The directory where files will be saved
       '''
    # make data dir, if it does not exist
    if not os.path.exists(data_dir):
        os.makedirs(data_dir)

    # combine labels and features
    pd.concat([y, x], axis=1)\
        .to_csv(os.path.join(data_dir, filename), header=False, index=False)

    # indicate function has run
    print('Path created: '+str(data_dir)+'/'+str(filename))
```

In [67]:
```
data_dir = 'starbucks_capstone_data' # the folder we will use for storing data in
name = 'train.csv'

# create 'train.csv'
make_csv(X_train, y_train, name, data_dir)
```

```
Path created: starbucks_capstone_data/train.csv
```

In [68]:
```
# prefix: description name for directory in S3
prefix = 'starbucks-capstone/offer-data'

# upload all data to S3
uploaded_data_s3 = sagemaker_session.upload_data(path=data_dir, bucket=bucket, ke
print(uploaded_data_s3)
```

```
s3://sagemaker-us-east-1-755811553671/starbucks-capstone/offer-data
```

In [69]:
```
# confirm that data is in S3 bucket
empty_check = []
for obj in boto3.resource('s3').Bucket(bucket).objects.all():
    empty_check.append(obj.key)
    print(obj.key)

assert len(empty_check) !=0, 'S3 bucket is empty.'
print('Test passed!')
```

```
pytorch-training-2020-03-17-23-51-43-608/source/sourcedir.tar.gz
pytorch-training-2020-03-18-01-11-58-026/source/sourcedir.tar.gz
sagemaker-pytorch-2020-03-12-22-51-57-034/source/sourcedir.tar.gz
sagemaker-pytorch-2020-03-12-22-56-39-650/sourcedir.tar.gz
sagemaker-pytorch-2020-03-12-23-43-44-272/source/sourcedir.tar.gz
sagemaker-pytorch-2020-03-12-23-48-27-357/sourcedir.tar.gz
sagemaker-pytorch-2020-03-12-23-51-58-595/source/sourcedir.tar.gz
sagemaker-pytorch-2020-03-13-00-02-31-894/source/sourcedir.tar.gz
sagemaker-pytorch-2020-03-13-00-12-14-586/source/sourcedir.tar.gz
sagemaker-pytorch-2020-03-13-00-22-30-980/source/sourcedir.tar.gz
sagemaker-pytorch-2020-03-13-00-32-02-350/sourcedir.tar.gz
sagemaker-pytorch-2020-03-16-23-37-24-421/source/sourcedir.tar.gz
sagemaker-pytorch-2020-03-16-23-47-41-276/sourcedir.tar.gz
sagemaker-pytorch-2020-03-17-23-59-58-298/sourcedir.tar.gz
sagemaker-pytorch-2020-03-18-01-20-12-705/sourcedir.tar.gz
sagemaker-record-sets/LinearLearner-2020-03-18-00-12-56-595/.amazon.manifest
sagemaker-record-sets/LinearLearner-2020-03-18-00-12-56-595/matrix_0.pbr
sagemaker-record-sets/LinearLearner-2020-03-18-00-18-26-009/.amazon.manifest
sagemaker-record-sets/LinearLearner-2020-03-18-00-18-26-009/matrix_0.pbr
```

Implementation

Define and Train Models

BenchMark Model - SVC

In [70]:
```
!pygmentize source_sklearn/train.py
```

```
from __future__ import print_function

import argparse
import os
import pandas as pd

from sklearn.externals import joblib

from sklearn.svm import SVC

# Model load function
def model_fn(model_dir):
    """Load model from the model_dir. This is the same model that is saved
    in the main if statement.
    """
    print("Loading model.")

    # load using joblib
    model = joblib.load(os.path.join(model_dir, "model.joblib"))
    print("Done loading model.")

    return model

# Main code
if __name__ == '__main__':

    # All of the model parameters and training parameters are sent as arguments
    # when this script is executed, during a training job

    # Set up an argument parser to easily access the parameters
    parser = argparse.ArgumentParser()

    # SageMaker parameters, like the directories for training data and saving m
odels; set automatically
    parser.add_argument('--output-data-dir', type=str, default=os.environ['SM_O
UTPUT_DATA_DIR'])
    parser.add_argument('--model-dir', type=str, default=os.environ['SM_MODEL_D
IR'])
    parser.add_argument('--data-dir', type=str, default=os.environ['SM_CHANNEL_
TRAIN'])

    # Additional Paramaters

    # args holds all passed-in arguments
    args = parser.parse_args()

    # Read in csv training file
    training_dir = args.data_dir
    train_data = pd.read_csv(os.path.join(training_dir, "train.csv"), header=No
ne, names=None)

    # Labels are in the first column
    train_y = train_data.iloc[:,0]
    train_x = train_data.iloc[:,1:]
```

```
    ## Define a model
    model = SVC()

    ## Train the model
    model.fit(train_x, train_y)

    # Save the trained model
    joblib.dump(model, os.path.join(args.model_dir, "model.joblib"))
```

In [71]:
```
from sagemaker.sklearn.estimator import SKLearn

estimator = SKLearn(entry_point='train.py',
                    source_dir='source_sklearn',
                    role=role,
                    train_instance_count=1,
                    train_instance_type='ml.c4.xlarge')
```

In [72]:
```
# Train estimator on S3 training data
estimator.fit({'train': uploaded_data_s3})
```

```
2020-03-20 20:30:03 Starting - Starting the training job...
2020-03-20 20:30:05 Starting - Launching requested ML instances......
2020-03-20 20:31:09 Starting - Preparing the instances for training...
2020-03-20 20:31:58 Downloading - Downloading input data......
2020-03-20 20:32:50 Training - Training image download completed. Training in
progress.2020-03-20 20:32:51,152 sagemaker-containers INFO     Imported frame
work sagemaker_sklearn_container.training
2020-03-20 20:32:51,154 sagemaker-containers INFO     No GPUs detected (norma
l if no gpus installed)
2020-03-20 20:32:51,164 sagemaker_sklearn_container.training INFO     Invokin
g user training script.
2020-03-20 20:32:51,628 sagemaker-containers INFO     Module train does not p
rovide a setup.py.
Generating setup.py
2020-03-20 20:32:51,629 sagemaker-containers INFO     Generating setup.cfg
2020-03-20 20:32:51,629 sagemaker-containers INFO     Generating MANIFEST.in
2020-03-20 20:32:51,629 sagemaker-containers INFO     Installing module with
 the following command:
/miniconda3/bin/python -m pip install .
```

In [73]:
```
%%time

# deploy model to create a predictor
predictor = estimator.deploy(initial_instance_count=1, instance_type='ml.t2.medi
```

```
-----------------!CPU times: user 307 ms, sys: 60 µs, total: 307 ms
Wall time: 8min 32s
```

In [74]:
```
# Determine accuracy of model
# First: generate predicted, class labels
test_y_preds = predictor.predict(X_test)
```

In [75]:
```
test_y = pd.DataFrame(y_test).iloc[:,0]
converted_test_y = test_y.reset_index(drop=True).values.astype(int)
```

In [76]:
```
# Second: calculate the test accuracy
accuracy = metrics.accuracy_score(converted_test_y, test_y_preds.round())
```

In [103]:
```
from sklearn.metrics import recall_score, precision_score,f1_score
recall = recall_score(test_y.values, test_y_preds)
precision = precision_score(test_y.values, test_y_preds)
f1_score = precision_score(test_y.values, test_y_preds)

print("\n{:<11} {:.3f}".format('Recall:', recall))
print("{:<11} {:.3f}".format('Precision:', precision))
print("{:<11} {:.3f}".format('Accuracy:', accuracy))
print("{:<11} {:.3f}".format('F1 Score:', f1_score))
```

```
Recall:     0.969
Precision:  0.859
Accuracy:   0.840
F1 Score:   0.859
```

Model 1 : PyTorch: Feed Forward Neural Network with 1 hidden layer

Create Pytorch estimator

In [78]:
```
!pygmentize source_pytorch/train.py
```

```
import argparse
import json
import os
import torch
import pandas as pd
import torch.nn as nn
import torch.optim as optim
import torch.utils.data

from model import BinaryClassifier

def model_fn(model_dir):
    """Load the PyTorch model from the `model_dir` directory."""
    print("Loading model.")

    # Load the parameters used to create the model
    model_info = {}
    model_info_path = os.path.join(model_dir, 'model_info.pth')
    with open(model_info_path, 'rb') as f:
```

In [79]:
```
# import a PyTorch wrapper
from sagemaker.pytorch import PyTorch

# specify an output path
output_path = 's3://{}/{}/{}'.format(bucket, prefix, "PyTorch")

feature_count = len(valid_offers_features.columns)
output_dim = 1

#Reference : https://www.heatonresearch.com/2017/06/01/hidden-layers.html
hidden_dim =   int( (2*feature_count)/3) + 1
print("Input Features:", feature_count, ", hidden_dim:", hidden_dim, ", output_d

# instantiate a pytorch estimator
estimator = PyTorch(entry_point='train.py',
                    source_dir='source_pytorch',
                    role=role,
                    framework_version='1.4.0',
                    train_instance_count=1,
                    train_instance_type='ml.p2.xlarge',
                    output_path=output_path,
                    sagemaker_session=sagemaker_session,
                    hyperparameters={
                        'input_features': feature_count, # number of features
                        'hidden_dim': hidden_dim,
                        'output_dim': output_dim,
                        'epochs': 26
                    })
```

```
Input Features: 14 , hidden_dim: 10 , output_dim: 1
```

Train the estimator

In [80]:
```
%%time
# train the estimator on S3 training data
estimator.fit({'train': uploaded_data_s3})
```

```
2020-03-20 20:42:21 Starting - Starting the training job...
2020-03-20 20:42:23 Starting - Launching requested ML instances.........
2020-03-20 20:44:05 Starting - Preparing the instances for training.........
2020-03-20 20:45:33 Downloading - Downloading input data...
2020-03-20 20:45:59 Training - Downloading the training image...........bash:
cannot set terminal process group (-1): Inappropriate ioctl for device
bash: no job control in this shell
2020-03-20 20:48:00,292 sagemaker-containers INFO     Imported framework sage
maker_pytorch_container.training
2020-03-20 20:48:00,321 sagemaker_pytorch_container.training INFO     Block u
ntil all host DNS lookups succeed.
2020-03-20 20:48:06,538 sagemaker_pytorch_container.training INFO     Invokin
g user training script.
2020-03-20 20:48:06,916 sagemaker-containers INFO     Module default_user_mod
ule_name does not provide a setup.py.
Generating setup.py
2020-03-20 20:48:06,916 sagemaker-containers INFO     Generating setup.cfg
2020-03-20 20:48:06,917 sagemaker-containers INFO     Generating MANIFEST.in
2020-03-20 20:48:06,917 sagemaker-containers INFO     Installing module with
```

Instantiate a PyTorchMode

In [81]:
```
!pygmentize source_pytorch/predict.py
```

```
# import libraries
import os
import numpy as np
import torch
from six import BytesIO

# import model from model.py, by name
from model import BinaryClassifier

# default content type is numpy array
NP_CONTENT_TYPE = 'application/x-npy'


# Model load function
def model_fn(model_dir):
    """Load the PyTorch model from the `model_dir` directory."""
    print("Loading model.")

    # Load the parameters used to create the model
    model_info = {}
    model_info_path = os.path.join(model_dir, 'model_info.pth')
    with open(model_info_path, 'rb') as f:
        model_info = torch.load(f)

    print("model_info: {}".format(model_info))

    # Determine the device and construct the model.
    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    model = BinaryClassifier(model_info['input_features'], model_info['hidden_d
im'], model_info['output_dim'])

    # Load the store model parameters.
    model_path = os.path.join(model_dir, 'model.pth')
    with open(model_path, 'rb') as f:
        model.load_state_dict(torch.load(f))

    # Prep for testing
    model.to(device).eval()

    print("Done loading model.")
    return model


# input data loading
def input_fn(serialized_input_data, content_type):
    print('Deserializing the input data.')
    if content_type == NP_CONTENT_TYPE:
        stream = BytesIO(serialized_input_data)

#         old = np.load
#         np.load = lambda *a,**k: old(*a,**k,allow_pickle=True)

        return np.load(stream)
    raise Exception('Requested unsupported ContentType in content_type: ' + con
tent_type)
```

```
# output data handling
def output_fn(prediction_output, accept):
    print('Serializing the generated output.')
    if accept == NP_CONTENT_TYPE:
        stream = BytesIO()
        np.save(stream, prediction_output)
        return stream.getvalue(), accept
    raise Exception('Requested unsupported ContentType in Accept: ' + accept)


# predict function
def predict_fn(input_data, model):
    print('Predicting class labels for the input data...')

    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

    # Process input_data so that it is ready to be sent to our model.
    data = torch.from_numpy(input_data.astype('float32'))
    data = data.to(device)

    # Put the model into evaluation mode
    model.eval()

    # Compute the result of applying the model to the input data
    # The variable `out_label` should be a rounded value, either 1 or 0
    out = model(data)
    out_np = out.cpu().detach().numpy()
    out_label = out_np.round()

    return out_label
```

In [82]:

```
from sagemaker.pytorch import PyTorchModel

# Create a model from the trained estimator data
# And point to the prediction script
model = PyTorchModel(model_data=estimator.model_data,
                     role=role,
                     framework_version='1.0',
                     entry_point='predict.py',
                     source_dir='source_pytorch')
```

Deploy Model

In [83]:

```
%%time
# deploy and create a predictor
predictor = model.deploy(initial_instance_count=1, instance_type='ml.m4.xlarge')
```

```
-------------!CPU times: user 368 ms, sys: 28 ms, total: 396 ms
Wall time: 6min 32s
```

In [84]:
```
# Convert test data
X_test_converted = X_test.reset_index(drop=True).values.astype(int)
y_test_converted = test_y.reset_index(drop=True).values.astype(int)
```

Evaluate against test set

In [86]:
```
# Evaluate the model
def evaluate(predictor, test_features, test_labels, verbose=True):
    """
    Evaluate a model on a test set given the prediction endpoint.
    Return binary classification metrics.
    :param predictor: A prediction endpoint
    :param test_features: Test features
    :param test_labels: Class labels for test data
    :param verbose: If True, prints a table of all performance metrics
    :return: A dictionary of performance metrics.
    """

    # rounding and squeezing array
    test_preds = np.squeeze(np.round(predictor.predict(test_features)))

    # calculate true positives, false positives, true negatives, false negatives
    tp = np.logical_and(test_labels, test_preds).sum()
    fp = np.logical_and(1-test_labels, test_preds).sum()
    tn = np.logical_and(1-test_labels, 1-test_preds).sum()
    fn = np.logical_and(test_labels, 1-test_preds).sum()

    if verbose:
        print("True Postives = ", tp)
        print("False Postives = ", fp)
        print("True Negatives = ", tn)
        print("False Negatives = ", fn)
        print()

    # calculate binary classification metrics
    recall = tp / (tp + fn)
    precision = tp / (tp + fp)
    accuracy = (tp + tn) / (tp + fp + tn + fn)
    f1_score = 2*( (precision * recall ) / (precision + recall) )

    # print metrics
    if verbose:
        print(pd.crosstab(test_labels, test_preds, rownames=['actuals'], colname
        print("\n{:<11} {:.3f}".format('Recall:', recall))
        print("{:<11} {:.3f}".format('Precision:', precision))
        print("{:<11} {:.3f}".format('Accuracy:', accuracy))
        print("{:<11} {:.3f}".format('F1 Score:', f1_score))
        print()

    return {'TP': tp, 'FP': fp, 'FN': fn, 'TN': tn,
            'Precision': precision, 'Recall': recall, 'Accuracy': accuracy, 'F1 
```

In [87]:
```
# get metrics for custom predictor
metrics = evaluate(predictor, X_test_converted, y_test_converted, True)
```

```
True Postives =  4689
False Postives =  900
True Negatives =  0
False Negatives =  0

predictions   1.0
actuals
0             900
1            4689

Recall:     1.000
Precision:  0.839
Accuracy:   0.839
F1 Score:   0.912
```

In [88]:
```
# Accepts a predictor endpoint as input
# And deletes the endpoint by name
def delete_endpoint(predictor):
        try:
            boto3.client('sagemaker').delete_endpoint(EndpointName=predictor.end
            print('Deleted {}'.format(predictor.endpoint))
        except:
            print('Already deleted: {}'.format(predictor.endpoint))
```

In [89]:
```
# delete the predictor endpoint
delete_endpoint(predictor)
```

```
Deleted sagemaker-pytorch-2020-03-20-20-51-07-411
```

Model 2 : LinearLearner with optimization for higher precision.

In [90]:
```
# import LinearLearner
from sagemaker import LinearLearner

# specify an output path
output_path = 's3://{}/{}/{}'.format(bucket, prefix, "LinearLearner")

# instantiate LinearLearner
linear = LinearLearner(role=role,
                       train_instance_count=1,
                       train_instance_type='ml.c4.xlarge',
                       predictor_type='binary_classifier',
                       optimizer = 'sgd',
                       output_path=output_path,
                       sagemaker_session=sagemaker_session,
                       epochs=50,
                       binary_classifier_model_selection_criteria='recall_at_tar
                       target_precision=0.9) # 90% precision)
```

In [91]:
```
# X_train, X_test, y_train, y_test

# convert features/labels to numpy
train_x_np = X_train.to_numpy().astype('float32')
train_y_np = y_train.to_numpy().astype('float32')

# create RecordSet
formatted_train_data = linear.record_set(train_x_np, labels=train_y_np)
```

In [92]:
```
%%time
# train the estimator on formatted training data
linear.fit(formatted_train_data)
```

```
2020-03-20 20:57:42 Starting - Starting the training job...
2020-03-20 20:57:44 Starting - Launching requested ML instances.........
2020-03-20 20:59:16 Starting - Preparing the instances for training......
2020-03-20 21:00:41 Downloading - Downloading input data
2020-03-20 21:00:41 Training - Downloading the training image..
2020-03-20 21:00:53 Training - Training image download completed. Training in
progress.Docker entrypoint called with argument(s): train
Running default environment configuration script
[03/20/2020 21:00:56 INFO 140007834728256] Reading default configuration from
/opt/amazon/lib/python2.7/site-packages/algorithm/resources/default-input.jso
n: {u'loss_insensitivity': u'0.01', u'epochs': u'15', u'feature_dim': u'aut
o', u'init_bias': u'0.0', u'lr_scheduler_factor': u'auto', u'num_calibration_
samples': u'10000000', u'accuracy_top_k': u'3', u'_num_kv_servers': u'auto',
 u'use_bias': u'true', u'num_point_for_scaler': u'10000', u'_log_level': u'in
fo', u'quantile': u'0.5', u'bias_lr_mult': u'auto', u'lr_scheduler_step': u'a
uto', u'init_method': u'uniform', u'init_sigma': u'0.01', u'lr_scheduler_mini
mum_lr': u'auto', u'target_recall': u'0.8', u'num_models': u'auto', u'early_s
topping_patience': u'3', u'momentum': u'auto', u'unbias_label': u'auto', u'w
d': u'auto', u'optimizer': u'auto', u'_tuning_objective_metric': u'', u'early
```

In [93]:
```
%%time
# deploy and create a predictor
linear_predictor = linear.deploy(initial_instance_count=1, instance_type='ml.t2.
```

```
-----------------!CPU times: user 333 ms, sys: 4.09 ms, total: 337 ms
Wall time: 8min 32s
```

In [94]:
```
# test one prediction
test_x_np = X_test.to_numpy().astype('float32')
result = linear_predictor.predict(test_x_np[0])

print(result)
```

```
[label {
  key: "predicted_label"
  value {
    float32_tensor {
      values: 1.0
    }
  }
}
label {
  key: "score"
  value {
    float32_tensor {
      values: 0.9570859670639038
    }
  }
}
]
```

In [95]:
```
# code to evaluate the endpoint on test data
# returns a variety of model metrics
def evaluate(predictor, test_features, test_labels, verbose=True):
    """
    Evaluate a model on a test set given the prediction endpoint.
    Return binary classification metrics.
    :param predictor: A prediction endpoint
    :param test_features: Test features
    :param test_labels: Class labels for test data
    :param verbose: If True, prints a table of all performance metrics
    :return: A dictionary of performance metrics.
    """

    # We have a lot of test data, so we'll split it into batches of 100
    # split the test data set into batches and evaluate using prediction endpoin
    prediction_batches = [predictor.predict(batch) for batch in np.array_split(te

    # LinearLearner produces a `predicted_label` for each data point in a batch
    # get the 'predicted_label' for every point in a batch
    test_preds = np.concatenate([np.array([x.label['predicted_label'].float32_ter
                                 for batch in prediction_batches])

    # calculate true positives, false positives, true negatives, false negatives
    tp = np.logical_and(test_labels, test_preds).sum()
    fp = np.logical_and(1-test_labels, test_preds).sum()
    tn = np.logical_and(1-test_labels, 1-test_preds).sum()
    fn = np.logical_and(test_labels, 1-test_preds).sum()

    # calculate binary classification metrics
    recall = tp / (tp + fn)
    precision = tp / (tp + fp)
    accuracy = (tp + tn) / (tp + fp + tn + fn)
    f1_score = 2*( (precision * recall ) / (precision + recall) )

    # printing a table of metrics
    if verbose:
        print(pd.crosstab(test_labels, test_preds, rownames=['actual (row)'], co
        print("\n{:<11} {:.3f}".format('Recall:', recall))
        print("{:<11} {:.3f}".format('Precision:', precision))
        print("{:<11} {:.3f}".format('Accuracy:', accuracy))
        print("{:<11} {:.3f}".format('f1_score:', f1_score))
        print()

    return {'TP': tp, 'FP': fp, 'FN': fn, 'TN': tn,
            'Precision': precision, 'Recall': recall, 'Accuracy': accuracy, 'f1_
```

In [96]:
```
print('Metrics for simple, LinearLearner.\n')

# get metrics for linear predictor
metrics = evaluate(linear_predictor,
                   X_test.to_numpy().astype('float32'),
                   y_test.to_numpy(),
                   verbose=True)
```

```
Metrics for simple, LinearLearner.

prediction (col)  0.0   1.0
actual (row)
0.0               423   477
1.0               522  4167

Recall:     0.889
Precision:  0.897
Accuracy:   0.821
f1_score:   0.893
```

In [97]:
```
# delete the predictor endpoint
delete_endpoint(linear_predictor)
```

```
Deleted linear-learner-2020-03-20-20-57-42-573
```

Refinement

For the models, epochs hyperparameter was optimised to identify optimium value where loss function does not decay further as measurable rate.

IV. Results

Model Evaluation and Validation

Metric	Benchmark - SVC	Neural Network	Linear Learner
Recall	0.969	1	0.889
Precision	0.859	0.839	0.897
Accuracy	0.84	0.839	0.821
F1 Score	0.859	0.912	0.893

Based on the metrics, LinearLearner model stands out for optimum value for precision and f1_score. There is no definite way to validate further the robustness of the model as we have only this limited data set.(sensitivity analysis) Neural network has very high recall, which tends to suggest for over fitting.

V. Conclusion

Reflection

This capstone challenge provided an oppurtunity to create complete end to end solution. Overall, I found the final solution (model) is able to capture the essence of problem and provide optimum strategies.

I believe business should be fine to send an offer to a customer in which he/she might be less intereted rather than not sending at all.

Improvement

Further refinement can be explored, where we can reduce the number of feature set to decrease bias and optimise precision. I did not see create specifically validation set due to limit amount of data available. I want to explore and provide more demographics insights and its impact on offer sent to customer.

References :


```
https://medium.com/kaggle-blog
https://elitedatascience.com/wp-content/uploads/2018/05/Feature-Engineering-Checklist.pdf
https://machinelearningmastery.com/understand-problem-get-better-results-using-exploratory-data-analysis/
https://towardsdatascience.com/why-automated-feature-engineering-will-change-the-way-you-do-machine-learning-5c15bf188b96
```