Json flattening

```
import os
os.chdir('D:/MSBA Classes/Fall/PREDITIVE/predictive project')
import json
import numpy as np
import pandas as pd
from pandas.io.json import json_normalize
```

Loading the train data in chunks

Concating the chunks into single Dataframe

```
In [3]:
chunk_list = []

for chunk in df_chunk:
    chunk_list.append(chunk)

train = pd.concat(chunk_list)
```

Removing the unwanted columns

```
In [4]:
    train = train.drop(['customDimensions','hits'], axis = 1)

In [6]:
    train.shape

Out[6]:
    (1708337, 11)

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

	channelGrouping	date	device	fullVisitorId	geoNetwork	socialEngagementType	totals	
0	Organic Search	20171016	{"browser": "Firefox", "browserVersion": "not	3162355547410993243	{"continent": "Europe", "subContinent": "Weste	Not Socially Engaged	{"visits": "1", "hits": "1", "pageviews": "1",	{"car "s
1	Referral	20171016	{"browser": "Chrome", "browserVersion": "not a	8934116514970143966	{"continent": "Americas", "subContinent": "Nor	Not Socially Engaged	{"visits": "1", "hits": "2", "pageviews": "2",	"/a/google.c
			7 111		7 11		70 1.10 0 0 0 0	

2	channelGrouping Direct	date 20171016	{"browser": "Cl derice , "browserVersion": "not a	fullVisitorId 7992466427990357681	{"continent": gealletwark, "subContinent": "Nor	socialEngagementType Not Socially Engaged	{"visits": "1", "hits totals , "pageviews": "2",	{"car
3	Organic Search	20171016	{"browser": "Chrome", "browserVersion": "not a	9075655783635761930	{"continent": "Asia", "subContinent": "Western	Not Socially Engaged	{"visits": "1", "hits": "2", "pageviews": "2",	{"car "s
4	Organic Search	20171016	{"browser": "Chrome", "browserVersion": "not a	6960673291025684308	{"continent": "Americas", "subContinent": "Cen	Not Socially Engaged	{"visits": "1", "hits": "2", "pageviews": "2",	{"car "s
4								Þ

Exporting the train data(reduced size) to csv

```
In [8]:
```

```
train.to_csv(r'D:/MSBA Classes/Fall/PREDITIVE/predictive project/train_json.csv')
```

Flattening of Json columns in train data

```
In [10]:

df.shape
```

Out[10]:

(1708337, 59)

In [11]:

df.head()

Out[11]:

	Unnamed: 0	channelGrouping	date	fullVisitorId	socialEngagementType	visitId	visitNumber	visitStartTime	devi
0	0	Organic Search	20171016	3162355547410993243	Not Socially Engaged	1508198450	1	1508198450	
1	1	Referral	20171016	8934116514970143966	Not Socially Engaged	1508176307	6	1508176307	
2	2	Direct	20171016	7992466427990357681	Not Socially Engaged	1508201613	1	1508201613	
3	3	Organic Search	20171016	9075655783635761930	Not Socially Engaged	1508169851	1	1508169851	
4	4	Organic Search	20171016	6960673291025684308	Not Socially Engaged	1508190552	1	1508190552	

5 rows × 59 columns

[4]

In []:

```
df.to_csv(r'D:/MSBA Classes/Fall/PREDITIVE/predictive project/train.csv')
```

Loading the test data in chunks

```
In [12]:
```

Concating the chunks into single Dataframe

```
In [13]:
```

```
chunk_list1 = []

for chunk in df_chunk:
    chunk_list1.append(chunk)

test = pd.concat(chunk_list1)
```

Removing the unwanted columns

```
In [14]:
```

```
test = test.drop(['customDimensions','hits'], axis = 1)
```

In [16]:

```
test.shape
Out[16]:
```

In [17]:

(401589, 11)

```
test.head()
```

Out[17]:

	channelGrouping	date	device	fullVisitorId	geoNetwork	socialEngagementType	totals	trafficSour
C	Organic Search	20180511	{"browser": "Chrome", "browserVersion": "not a	7460955084541987166	{"continent": "Asia", "subContinent": "Souther	Not Socially Engaged	{"visits": "1", "hits": "4", "pageviews": "3",	{"referralPat "(not set "campaign" (no
1	Direct	20180511	{"browser": "Chrome", "browserVersion": "not a	460252456180441002	{"continent": "Americas", "subContinent": "Nor	Not Socially Engaged	{"visits": "1", "hits": "4", "pageviews": "3",	{"referralPat "(not se "campaign (no
2	de Organic Search	20180511	{"browser": "Chrome", "browserVersion": "not a	3461808543879602873	{"continent": "Americas", "subContinent": "Nor	Not Socially Engaged	{"visits": "1", "hits": "4", "pageviews": "3",	{"referralPat "(not se "campaign (no
3	B Direct	20180511	{"browser": "Chrome", "browserVersion": "not a	975129477712150630	{"continent": "Americas", "subContinent": "Nor	Not Socially Engaged	{"visits": "1", "hits": "5", "pageviews": "4",	{"referralPat "(not se "campaign (no
4	Organic Search	20180511	{"browser": "Internet Explorer", "browserVersi	8381672768065729990	{"continent": "Americas", "subContinent": "Nor	Not Socially Engaged	{"visits": "1", "hits": "5", "pageviews": "4",	{"referralPat "(not se "campaign (no
4								Þ

```
test.to csv(r'D:/MSBA Classes/Fall/PREDITIVE/predictive project/test json.csv')
Flattening of Json columns in test data
In [19]:
df2 = pd.read csv('test json.csv',
                       converters={column: json.loads for column in JSON_COLUMNS},
                       dtype={'fullVisitorId': 'str'}, # Important!!
for column in JSON COLUMNS:
        column as df = json normalize(df2[column])
         column_as_df.columns = [f"{column}.{subcolumn}" for subcolumn in column_as_df.columns]
        df2 = df2.drop(column, axis=1).merge(column_as_df, right_index=True, left_index=True)
In [20]:
df2.shape
Out[20]:
(401589, 58)
In [21]:
df2.head()
Out[21]:
   Unnamed:
            channelGrouping
                               date
                                            fullVisitorId socialEngagementType
                                                                              visitId visitNumber visitStartTime devi-
               Organic Search 20180511 7460955084541987166
                                                         Not Socially Engaged 1526099341
                                                                                                 1526099341
          1
                     Direct 20180511 460252456180441002
                                                         Not Socially Engaged 1526064483
                                                                                           166
                                                                                                 1526064483
              Organic Search 20180511 3461808543879602873
                                                         Not Socially Engaged 1526067157
                                                                                                 1526067157
          3
                      Direct 20180511 975129477712150630
                                                         Not Socially Engaged 1526107551
                                                                                                 1526107551
              Organic Search 20180511 8381672768065729990
                                                         Not Socially Engaged 1526060254
                                                                                                 1526060254
5 rows × 58 columns
In [ ]:
df2.to csv(r'D:/MSBA Classes/Fall/PREDITIVE/predictive project/test.csv')
```

Predictive-GA Prediction_latest

In [18]:

```
Data Cleaning & Transformation

In [1]:

# import packages

import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime, timedelta
```

In [2]:

```
# Read train data
train = pd.read_csv("train.csv", low_memory = False)
```

In [3]:

```
pd.set_option('display.max_columns', 500)
```

In [4]:

train.head()

Out[4]:

	Unnamed: 0	Unnamed: 0.1	channelGrouping	date	fullVisitorId	socialEngagementType	visitld	visitNumber	visitStaı
0	0	0	Organic Search	20171016	3162355547410993243	Not Socially Engaged	1508198450	1	15081
1	1	1	Referral	20171016	8934116514970143966	Not Socially Engaged	1508176307	6	15081
2	2	2	Direct	20171016	7992466427990357681	Not Socially Engaged	1508201613	1	15082
3	3	3	Organic Search	20171016	9075655783635761930	Not Socially Engaged	1508169851	1	15081
4	4	4	Organic Search	20171016	6960673291025684308	Not Socially Engaged	1508190552	1	15081
4									Þ

In [5]:

```
# Read test data
test = pd.read_csv("test.csv", low_memory = False)
```

In [6]:

```
test.head()
```

Out[6]:

	Unnamed: 0	Unnamed: 0.1	channelGrouping	date	fullVisitorId	socialEngagementType	visitld	visitNumber	visitStaı
0	0	0	Organic Search	20180511	7460955084541987166	Not Socially Engaged	1526099341	2	15260
1	1	1	Direct	20180511	460252456180441002	Not Socially Engaged	1526064483	166	15260
2	2	2	Organic Search	20180511	3461808543879602873	Not Socially Engaged	1526067157	2	15260
3	3	3	Direct	20180511	975129477712150630	Not Socially Engaged	1526107551	4	15261
4	4	4	Organic Search	20180511	8381672768065729990	Not Socially Engaged	1526060254	1	15260
4									Þ

In [7]:

```
# Drop unnnamed columns
train = train.drop(['Unnamed: 0', 'Unnamed: 0.1'], axis=1)
test = test.drop(['Unnamed: 0', 'Unnamed: 0.1'], axis=1)
```

```
In [8]:
# Find data shape
print('Train shape:', train.shape)
print('Test shape:', test.shape)
Train shape: (1708337, 58)
Test shape: (401589, 57)
In [9]:
# Find data type
print(train.dtypes.value_counts())
           42
object
float64
           9
int64
bool
            1
dtype: int64
In [10]:
col_with_constant = pd.DataFrame({'uniq_counts': [col for col in train.columns if train[col].nuniqu
e() == 1] )
print("Columns with constant value: ", len(col with constant), "columns")
print("Name of constant columns: \n", col with constant)
Columns with constant value: 24 columns
Name of constant columns:
                                            uniq_counts
0
                                 socialEngagementType
1
                                 device.browserVersion
2
                                    device.browserSize
                        device.operatingSystemVersion
4
                          device.mobileDeviceBranding
5
                             device.mobileDeviceModel
                            device.mobileInputSelector
7
                              device.mobileDeviceInfo
8
                     device.mobileDeviceMarketingName
9
                                   device.flashVersion
10
                                       device.language
11
                                   device.screenColors
12
                               device.screenResolution
1.3
                                    geoNetwork.cityId
14
                                   geoNetwork.latitude
15
                                  geoNetwork.longitude
16
                           geoNetwork.networkLocation
17
                                         totals.visits
18
                                        totals.bounces
19
                                      totals.newVisits
20 trafficSource.adwordsClickInfo.criteriaParameters
21
                           trafficSource.isTrueDirect
22
             trafficSource.adwordsClickInfo.isVideoAd
2.3
                            trafficSource.campaignCode
In [11]:
constant cols = col with constant['uniq counts'].tolist()
constant_df = train[constant_cols]
constant df.head()
```

Out[11]:

2

Not Socially Engaged

	socialEngagementType	device.browserVersion	device.browserSize	device.operatingSystemVersion	device.mobileDeviceBranding	dev
0	Not Socially Engaged	not available in demo dataset	not available in demo dataset	not available in demo dataset	not available in demo dataset	
1	Not Socially Engaged	not available in demo dataset	not available in demo dataset	not available in demo dataset	not available in demo dataset	

not available in demo dataset

not available in demo dataset

not available in

demo dataset

not available in demo

```
socialEngagementType device browser Version device browser Size device operating System Version device mobile Device Branding
                                       dataset
                                                     demo dataset
                             not available in demo
                                                    not available in
       Not Socially Engaged
                                                                      not available in demo dataset
                                                                                                 not available in demo dataset
                                                     demo dataset
                                       dataset
4
In [12]:
drop = ['totals.visits', 'totals.bounces', 'totals.newVisits']
for i in drop:
     constant_cols.remove(i)
In [13]:
 # drop columns with constant value from train data
```

In [14]:

```
# drop columns with constant value from test data
col_with_constant_t = pd.DataFrame({'uniq_counts': [col for col in test.columns if test[col].nuniqu
e() == 1]})
print("Columns with constant value: ", len(col_with_constant_t), "columns")
print("Name of constant columns: \n", col_with_constant_t)
```

Columns with constant value: 23 columns Name of constant columns: uniq_counts 0 socialEngagementType 1 device.browserSize 2 device.browserVersion 3 device.flashVersion device.language 5 device.mobileDeviceBranding 6 device.mobileDeviceInfo device.mobileDeviceMarketingName 8 device.mobileDeviceModel device.mobileInputSelector 10 device.operatingSystemVersion 11 device.screenColors 12 device.screenResolution 1.3 geoNetwork.cityId 14 geoNetwork.latitude 15 geoNetwork.longitude

trafficSource.adwordsClickInfo.criteriaParameters

trafficSource.adwordsClickInfo.isVideoAd

train = train.drop(columns = constant cols, axis=1)

In [15]:

16

17

18

19

20

21

22

```
constant_cols_t = col_with_constant_t['uniq_counts'].tolist()
constant_df_t = test[constant_cols_t]
constant_df_t.head()
```

geoNetwork.networkLocation

trafficSource.isTrueDirect

totals.bounces

totals.visits

totals.newVisits

Out[15]:

	socialEngagementType	device.browserSize	device.browserVersion	device.flashVersion	device.language	device.mobileDeviceBranding
0	Not Socially Engaged	not available in demo dataset	not available in demo dataset	not available in demo dataset	not available in demo dataset	not available in demo datase
1	Not Socially Engaged	not available in demo dataset	not available in demo dataset	not available in demo dataset	not available in demo dataset	not available in demo datase
2	Not Socially Engaged	not available in demo dataset	not available in demo dataset	not available in demo dataset	not available in demo dataset	not available in demo datase
3	Not Socially Engaged	not available in demo dataset	not available in demo dataset	not available in demo dataset	not available in demo dataset	not available in demo datase

```
not available in demo
device.browserVersion
dataset
                                                                               not available in device language
 4 sociate Agaigum Engreped device the mysterial set
                                                             not available in
device.tlashVersion
denio dalaset
                                                                                               device analythe Dievice Braheting
4
In [94]:
constant_cols_t
Out[94]:
['socialEngagementType',
  'device.browserSize',
  'device.browserVersion',
 'device.flashVersion',
 'device.language',
 'device.mobileDeviceBranding',
  'device.mobileDeviceInfo',
  'device.mobileDeviceMarketingName',
 'device.mobileDeviceModel',
 'device.mobileInputSelector',
 'device.operatingSystemVersion',
  'device.screenColors',
  'device.screenResolution',
  'geoNetwork.cityId',
 'geoNetwork.latitude',
 'geoNetwork.longitude',
  'geoNetwork.networkLocation',
  'trafficSource.adwordsClickInfo.criteriaParameters',
  'trafficSource.adwordsClickInfo.isVideoAd',
 'trafficSource.isTrueDirect']
In [16]:
drop = ['totals.visits', 'totals.bounces', 'totals.newVisits']
for i in drop:
     constant cols t.remove(i)
 # drop columns with constant value from train data
test = test.drop(columns = constant_cols_t, axis=1)
In [17]:
test.head()
Out[17]:
    channelGrouping
                       date
                                     fullVisitorId
                                                     visitId visitNumber visitStartTime device.browser device.deviceCategory
      Organic Search 20180511 7460955084541987166 1526099341
                                                                         1526099341
 0
                                                                    2
                                                                                          Chrome
                                                                                                                mobile
             Direct 20180511
                             460252456180441002 1526064483
                                                                   166
                                                                         1526064483
                                                                                          Chrome
                                                                                                               desktop
      Organic Search 20180511 3461808543879602873 1526067157
                                                                         1526067157
                                                                                                               desktop
 2
                                                                    2
                                                                                          Chrome
 3
             Direct 20180511
                             975129477712150630 1526107551
                                                                    4
                                                                         1526107551
                                                                                          Chrome
                                                                                                                mobile
                                                                                          Internet
      Organic Search 20180511 8381672768065729990 1526060254
                                                                         1526060254
                                                                                                                tablet
                                                                                          Explorer
4
In [18]:
# Print data shape after dropping constant columns
print('Train shape:', train.shape)
print('Test shape:', test.shape)
Train shape: (1708337, 37)
Test shape: (401589, 37)
In [19]:
 # Find if there's missing value in data
```

```
def find missing(data):
    #find the features that have missing values
    count missing=data.isnull().sum().values
    total=data.shape[0]
    ratio missing=count missing/total
    return pd.DataFrame({'missing_count':count_missing,'missing_ratio':ratio_missing},
                                   index=data.columns.values)
train missing=find missing(train)
test_missing=find_missing(test)
#merge the train and test missing ratio
train_missing.reset_index()[['index','missing_ratio']].merge(test_missing.reset_index()[['index','
missing_ratio']],on='index',how='left')\
                  .rename(columns={'index':'columns','missing ratio x':'train missing ratio','missi
ng_ratio_y':'test_missing_ratio'})\
                  .sort values(['train missing ratio','test missing ratio'], ascending=False).query(
'train missing ratio>0')
```

Out[19]:

	columns	train_missing_ratio	test_missing_ratio
25	totals.transactionRevenue	0.989163	0.988560
26	totals.totalTransactionRevenue	0.989163	0.988560
24	totals.transactions	0.989136	0.984300
32	trafficSource.adContent	0.962105	0.000000
33	trafficSource.adwordsClickInfo.page	0.955937	0.973592
34	traffic Source. adwords ClickInfo. slot	0.955937	0.973592
36	traffic Source. adwords Click Info. ad Network Type	0.955937	0.973592
35	trafficSource.adwordsClickInfo.gclld	0.955850	0.973575
31	trafficSource.referralPath	0.668529	0.000000
30	trafficSource.keyword	0.616260	0.100167
23	totals.timeOnSite	0.511781	0.457398
20	totals.bounces	0.489809	0.545112
22	totals.sessionQualityDim	0.488940	0.000000
21	totals.newVisits	0.234677	0.287667

totals.pageviews

In [20]:

19

```
# Find numerical columns in train data
numeric_features_train = train.select_dtypes(include=[np.number])
numeric_features_train.columns
```

0.000252

0.000140

Out[20]:

In [21]:

```
# Find numerical columns in test data
numeric_features_test = test.select_dtypes(include=[np.number])
numeric_features_test.columns
```

Out[21]:

```
'totals.transactions', 'totals.visits',
       'trafficSource.adwordsClickInfo.page'],
      dtype='object')
In [22]:
# Find categorical columns in train data
categorical_features_train = train.select_dtypes(include=[np.object])
categorical_features_train.columns
Out[22]:
Index(['channelGrouping', 'fullVisitorId', 'device.browser',
        'device.operatingSystem', 'device.deviceCategory',
       'geoNetwork.continent', 'geoNetwork.subContinent', 'geoNetwork.country',
       'geoNetwork.region', 'geoNetwork.metro', 'geoNetwork.city',
       'geoNetwork.networkDomain', 'trafficSource.campaign',
        'trafficSource.source', 'trafficSource.medium', 'trafficSource.keyword',
       'trafficSource.referralPath', 'trafficSource.adContent',
       'trafficSource.adwordsClickInfo.slot',
       'trafficSource.adwordsClickInfo.gclId',
       'trafficSource.adwordsClickInfo.adNetworkType'],
      dtype='object')
In [23]:
# Find categorical columns in test data
categorical features test = test.select dtypes(include=[np.object])
categorical features test.columns
Out[23]:
Index(['channelGrouping', 'fullVisitorId', 'device.browser',
        'device.deviceCategory', 'device.operatingSystem', 'geoNetwork.city',
        'geoNetwork.continent', 'geoNetwork.country', 'geoNetwork.metro',
        'geoNetwork.networkDomain', 'geoNetwork.region',
        'geoNetwork.subContinent', 'trafficSource.adContent',
       'trafficSource.adwordsClickInfo.adNetworkType',
       'trafficSource.adwordsClickInfo.gclId',
       'trafficSource.adwordsClickInfo.slot', 'trafficSource.campaign',
       'trafficSource.keyword', 'trafficSource.medium',
       'trafficSource.referralPath', 'trafficSource.source'],
      dtype='object')
In [24]:
miss cols = ['trafficSource.adContent', 'trafficSource.adContent',
'trafficSource.adwordsClickInfo.page',
'trafficSource.adwordsClickInfo.slot', 'trafficSource.adwordsClickInfo.adNetworkType',
'trafficSource.adwordsClickInfo.gclId', 'trafficSource.referralPath', 'trafficSource.keyword', 'totals.timeOnSite', 'totals.bounces', 'totals.sessionQualityDim', 'totals.newVisits',
'totals.pageviews']
In [25]:
len(miss cols)
Out.[251:
1.3
In [26]:
num_cols = numeric_features_train.columns.tolist()
In [27]:
for col in miss cols:
    print(col, pd.DataFrame(train[col].unique()))
```

```
trafficSource.adContent
                                                           0
0
    Placement Accessories 300 x 250
1
2
         Google Merchandise Store
3
                      Bags 300x250
         Display Ad created 3/11/14
4
                     GA Help Center
72
73
                     Free Shipping!
74
               Swag w/ Google Logos
          Men's Apparel from Google
75
                   Ad from 2/17/17
[77 rows x 1 columns]
trafficSource.adContent
0
                                NaN
    Placement Accessories 300 x 250
1
         Google Merchandise Store
                       Bags 300x250
.3
4
         Display Ad created 3/11/14
                     GA Help Center
72
73
                     Free Shipping!
74
               Swag w/ Google Logos
75
          Men's Apparel from Google
76
                    Ad from 2/17/17
[77 rows x 1 columns]
trafficSource.adwordsClickInfo.page
0
    NaN
1
    1.0
2
    3.0
    2.0
3
    5.0
5
   6.0
    4.0
6
    14.0
8
     7.0
9
    8.0
10 9.0
11 12.0
trafficSource.adwordsClickInfo.slot
                                                             0
0
                      NaN
1
                      Top
3 Google Display Network
trafficSource.adwordsClickInfo.adNetworkType
                                                               0
0
              NaN
1
     Google Search
2
          Content
3 Search partners
                                                                                              Ω
trafficSource.adwordsClickInfo.gclId
1
       Cj0KCQjwsZHPBRClARIsAC-VMPBHdNF2oMOgh6Xp6YhjXW...
                              CODVoMjJ9tYCFUIvqQod dsKEA
2
       CjOKCQjwsZHPBRClARIsAC-VMPA4CVJtDhu1lYkB0AR1hj...
       CjOKCQjwsZHPBRClARIsAC-VMPDlLD6kS4tmqFGZjMUqye...
4
. . .
59004 CjwKEAiA17LDBRDElqOGq8vR7m8SJAA1AC0 L8MUnlMT5A...
59005 CjwKEAiA17LDBRDElqOGq8vR7m8SJAA1AC0 aFaq6n49gX...
59006 CjwKEAiA17LDBRDElqOGq8vR7m8SJAA1AC0 F8I700U-81...
59007 CjwKEAiA17LDBRDElqOGq8vR7m8SJAA1AC0 HT9qtS8geJ...
59008 CjwKEAiA17LDBRDElqOGq8vR7m8SJAA1AC0_0wzbDX0fd-...
[59009 rows x 1 columns]
trafficSource.referralPath
                                                                                   0
      /a/google.com/transportation/mtv-services/bike...
1
2
                                             /offer/2145
      /a/google.com/nest-vision/dropcam-field-tester...
                                        /analytics/web/
4
                    /intl/ar/yt/advertise/how-it-works/
3192
3193
                             /yt/lineups/ru/france.html
3194
                                        /mail/mu/mp/118/
3195
                                             /BB1QfReObs
3196
                                        /mail/mu/mp/509/
```

```
, mall, mp, oo,
[3197 rows x 1 columns]
trafficSource.keyword
                                                          0
                         water bottle
1
2
                       (not provided)
      (Remarketing/Content targeting)
4
                     6qEhsCssdK0z36ri
. . .
4542
                           www googl
4543
       global corporate merchandise
4544
                            Mug pic
4545
                      shorter google
4546
              google shirts for sale
[4547 rows x 1 columns]
totals.timeOnSite
       NaN
1
       28.0
      38.0
2
        1.0
      52.0
4
4770 5564.0
4771 3587.0
4772 4665.0
4773 5381.0
4774 8811.0
[4775 rows x 1 columns]
totals.bounces 0
0 1.0
1 NaN
totals.sessionQualityDim
  1.0
     2.0
1
2
      3.0
3
      4.0
     6.0
4
       . . .
     95.0
96
     97.0
97
98
     99.0
99
    98.0
100 100.0
[101 rows x 1 columns]
totals.newVisits 0
0 1.0
1 NaN
totals.pageviews
    1.0
0
      2.0
1
      3.0
      4.0
     5.0
226 232.0
227 429.0
228 213.0
229 151.0
230 186.0
[231 rows x 1 columns]
In [28]:
# Fill nan numeric value with zero
miss col num = ['trafficSource.adwordsClickInfo.page', 'totals.timeOnSite', 'totals.bounces', 'total
ls.sessionQualityDim', 'totals.newVisits',
              'totals.pageviews']
def fill na num(df):
```

for col in miss_col_num:

df[col] = train[col].fillna(0).astype(int)

In [29]:

```
train.head()
```

Out[29]:

	channelGrouping	date	fullVisitorId	visitld	visitNumber	visitStartTime	device.browser	device.operatingSystem
0	Organic Search	20171016	3162355547410993243	1508198450	1	1508198450	Firefox	Windows
1	Referral	20171016	8934116514970143966	1508176307	6	1508176307	Chrome	Chrome OS
2	Direct	20171016	7992466427990357681	1508201613	1	1508201613	Chrome	Android
3	Organic Search	20171016	9075655783635761930	1508169851	1	1508169851	Chrome	Windows
4	Organic Search	20171016	6960673291025684308	1508190552	1	1508190552	Chrome	Windows
4								Þ

In [30]:

```
cat cols = ['channelGrouping',
'device.browser',
'device.isMobile',
'device.operatingSystem',
'device.deviceCategory',
'geoNetwork.continent',
'geoNetwork.subContinent',
 'geoNetwork.country',
'geoNetwork.region',
'geoNetwork.etro',
'geoNetwork.city',
 'geoNetwork.networkDomain',
 'trafficSource.campaign',
'trafficSource.source',
'trafficSource.medium',
'trafficSource.keyword',
'trafficSource.referralPath',
'trafficSource.adContent',
'trafficSource.adwordsClickInfo.slot',
'trafficSource.adwordsClickInfo.gclId',
'trafficSource.adwordsClickInfo.adNetworkType']
```

In [31]:

```
train.head()
```

Out[31]:

	channelGrouping	date	fullVisitorId	visitId	visitNumber	visitStartTime	device.browser	device.operatingSystem
0	Organic Search	20171016	3162355547410993243	1508198450	1	1508198450	Firefox	Windows
1	Referral	20171016	8934116514970143966	1508176307	6	1508176307	Chrome	Chrome OS
2	Direct	20171016	7992466427990357681	1508201613	1	1508201613	Chrome	Android
3	Organic Search	20171016	9075655783635761930	1508169851	1	1508169851	Chrome	Windows
4	Organic Search	20171016	6960673291025684308	1508190552	1	1508190552	Chrome	Windows
4								Þ

In [32]:

```
test.head()
```

	channelGrouping	date	fullVisitorId	visitld	visitNumber	visitStartTime	device.browser	device.deviceCategory
0	Organic Search	20180511	7460955084541987166	1526099341	2	1526099341	Chrome	mobile
1	Direct	20180511	460252456180441002	1526064483	166	1526064483	Chrome	desktop
2	Organic Search	20180511	3461808543879602873	1526067157	2	1526067157	Chrome	desktop
3	Direct	20180511	975129477712150630	1526107551	4	1526107551	Chrome	mobile
4	Organic Search	20180511	8381672768065729990	1526060254	1	1526060254	Internet Explorer	tablet
4								Þ
T	1241.							

In [34]:

```
# Transfer datetime data
def date_converter(df):
    df['date'] = df['date'].astype(str)
    df["date"] = df["date"].apply(lambda x : x[:4] + "-" + x[4:6] + "-" + x[6:])
    df["date"] = pd.to_datetime(df["date"])

return df
```

In [35]:

```
train_2 = date_converter(train)
```

In [36]:

```
test_2 = date_converter(test)
```

In [37]:

```
train_2 = test.reindex(sorted(train.columns), axis = 1)
test_2 = test.reindex(sorted(test.columns), axis = 1)
```

In [38]:

```
data = pd.concat([train_2, test_2])
```

In [39]:

```
data.head()
```

Out[39]:

	channelGrouping	date	device.browser	device.deviceCategory	device.isMobile	device.operatingSystem	fullVisitorId	geol
0	Organic Search	2018- 05-11	Chrome	mobile	True	Android	7460955084541987166	
1	Direct	2018- 05-11	Chrome	desktop	False	Macintosh	460252456180441002	S
2	Organic Search	2018- 05-11	Chrome	desktop	False	Chrome OS	3461808543879602873	nc (
3	Direct	2018- 05-11	Chrome	mobile	True	iOS	975129477712150630	
4	Organic Search	2018- 05-11	Internet Explorer	tablet	True	Windows	8381672768065729990	
4								Þ

In [40]:

```
num_cols = ['totals.visits', 'totals.hits', 'totals.pageviews', 'totals.bounces', 'totals.newVisits
', 'totals.sessionQualityDim', 'totals.timeOnSite', 'totals.transactions',
'totals.transactionRevenue', 'totals.totalTransactionRevenue']
```

```
for col in num cols:
      data[col] = data[col].fillna(0)
In [41]:
data['device.isMobile'] = data['device.isMobile'].map({True:1,False:0})
In [42]:
data.columns
Out[42]:
Index(['channelGrouping', 'date', 'device.browser', 'device.deviceCategory',
            'device.isMobile', 'device.operatingSystem', 'fullVisitorId',
           'geoNetwork.city', 'geoNetwork.continent', 'geoNetwork.country', 'geoNetwork.metro', 'geoNetwork.networkDomain', 'geoNetwork.region',
           'geoNetwork.subContinent', 'totals.bounces', 'totals.hits',
           'totals.newVisits', 'totals.pageviews', 'totals.sessionQualityDim',
           'totals.timeOnSite', 'totals.totalTransactionRevenue',
            'totals.transactionRevenue', 'totals.transactions', 'totals.visits',
            'trafficSource.adContent',
           'trafficSource.adwordsClickInfo.adNetworkType',
           'trafficSource.adwordsClickInfo.gclId',
           'trafficSource.adwordsClickInfo.page',
           'trafficSource.adwordsClickInfo.slot', 'trafficSource.campaign',
           'trafficSource.keyword', 'trafficSource.medium',
           'trafficSource.referralPath', 'trafficSource.source', 'visitId',
           'visitNumber', 'visitStartTime'],
         dtype='object')
In [48]:
def advance tranformation(data, k):
      date min = data['date'].min()
      date max = data['date'].max()
      df = data[(data['date'] >= date min + timedelta(168 * (k-1))) & (data['date'] < date min + timedelta(168 * (k-1))) & (data['date'] < date min + timedelta(168 * (k-1))) & (data['date'] < date min + timedelta(168 * (k-1))) & (data['date'] < date min + timedelta(168 * (k-1))) & (data['date'] < date min + timedelta(168 * (k-1))) & (data['date'] < date min + timedelta(168 * (k-1))) & (data['date'] < date min + timedelta(168 * (k-1)))) & (data['date'] < date min + timedelta(168 * (k-1)))) & (data['date'] < date min + timedelta(168 * (k-1)))) & (data['date'] < date min + timedelta(168 * (k-1)))) & (data['date'] < date min + timedelta(168 * (k-1)))) & (data['date'] < date min + timedelta(168 * (k-1)))) & (data['date'] < date min + timedelta(168 * (k-1)))) & (data['date'] < date min + timedelta(168 * (k-1)))) & (data['date'] < date min + timedelta(168 * (k-1)))) & (data['date'] < date min + timedelta(168 * (k-1)))) & (data['date'] < date min + timedelta(168 * (k-1)))) & (data['date'] < date min + timedelta(168 * (k-1)))) & (data['data(168 * (k-1))]) &
timedelta(days=168 * k))]
      df future id = pd.unique(data[(data['date'] >= date min + timedelta(days = 168 * k + 46)) & (da
ta['date'] < date min + timedelta(days=168 * k + 46 + 62))]['fullVisitorId'])</pre>
      df_return = df[df['fullVisitorId'].isin(df_future_id)]
      return unique = pd.unique(df return['fullVisitorId'])
      df test = data[(data['fullVisitorId'].isin(return unique))]
      df test = df test[(df test['date'] >= date min + timedelta(days = 168 * k + 46)) & (df test['da
te'] < date min + timedelta(days=168 * k + 46 + 62))]</pre>
      df target = df test.groupby('fullVisitorId').apply(lambda x:
np.log1p(sum(x['totals.transactionRevenue']))).reset_index()
      df_target['ret'] = 1
      df target = df target.rename(columns= {0: 'target'})
      df not return = df[df['fullVisitorId'].isin(df future id) == False]
      not return unique = pd.unique(df not return['fullVisitorId'])
      df_not_ret_df = pd.DataFrame({'fullVisitorId': not_return_unique, 'target': 0, 'ret': 0})
      target_df = pd.concat([df_target, df_not_ret_df])
      df_group = pd.DataFrame()
      df group['channelGrouping'] = df.groupby('fullVisitorId').agg(lambda x: x['channelGrouping'].mo
de()[0])['channelGrouping']
      df group['first ses from the period start'] = df['date'].min() - date min
      df group['last ses from the period end'] = date max - df['date'].max()
      df group['interval dates'] = df['date'].max() - df['date'].min()
      df group['unique date num'] = len(pd.unique(df['date']))
      df_group['maxVisitNum'] = df.groupby('fullVisitorId')['totals.visits'].agg("max")
      df group['browser'] = df.groupby('fullVisitorId').agg(lambda x: x['device.browser'].mode()[0])[
'device.browser']
      df group['operatingSystem'] = df.groupby('fullVisitorId').agg(lambda x:
x['device.operatingSystem'].mode()[0])['device.operatingSystem']
      df_group['deviceCategory'] = df.groupby('fullVisitorId').agg(lambda x:
x['device.deviceCategory'].mode()[0])['device.deviceCategory']
      df group['continent'] = df.groupby('fullVisitorId').agg(lambda x: x['geoNetwork.continent'].mod
e()[0])['geoNetwork.continent']
      df group['subContinent'] = df.groupby('fullVisitorId').agg(lambda x:
x['geoNetwork.subContinent'].mode()[0])['geoNetwork.subContinent']
```

```
df group['country'] = df.groupby('fullVisitorId').agg(lambda x: x['geoNetwork.country'].mode()[
0])['geoNetwork.country']
    df group['region'] = df.groupby('fullVisitorId').agg(lambda x: x['geoNetwork.region'].mode()[0]
)['geoNetwork.region']
    df group['metro'] = df.groupby('fullVisitorId').agg(lambda x: x['geoNetwork.metro'].mode()[0])[
'geoNetwork.metro'l
    df group['city'] = df.groupby('fullVisitorId').agg(lambda x: x['geoNetwork.city'].mode()[0])['g
eoNetwork.city']
    df_group['networkDomain'] = df.groupby('fullVisitorId').agg(lambda x:
x['geoNetwork.networkDomain'].mode()[0])['geoNetwork.networkDomain']
    df group['source'] = df.groupby('fullVisitorId').agg(lambda x: x['trafficSource.source'].mode()
[0])['trafficSource.source']
    df_group['medium'] = df.groupby('fullVisitorId').agg(lambda x: x['trafficSource.medium'].mode()
[0])['trafficSource.medium']
    df group['isMobile'] = df.groupby('fullVisitorId')['device.isMobile'].agg("sum")
    df group['bounce sessions'] = df.groupby('fullVisitorId')['totals.bounces'].agg("sum")
    df group['hits sum'] = df.groupby('fullVisitorId')['totals.hits'].agg("sum")
    df_group['hits_mean'] = df.groupby('fullVisitorId')['totals.hits'].agg("mean")
    df_group['pageviews_sum'] = df.groupby('fullVisitorId')['totals.pageviews'].agg("sum")
    df group['pageviews mean'] = df.groupby('fullVisitorId')['totals.pageviews'].agg("mean")
    df group['session cnt'] = len(df['visitStartTime'])
    df group['transactionRevenue'] = df.groupby('fullVisitorId')['totals.transactionRevenue'].agg("
sum")
    df group['transactions'] = df.groupby('fullVisitorId')['totals.transactions'].agg("sum")
    df group = pd.merge(df group, target df, on='fullVisitorId', sort=False)
    return df_group
4
In [49]:
tr_1 = advance_tranformation(data, 1)
tr_2 = advance_tranformation(data, 2)
tr 3 = advance tranformation(data, 3)
tr 4 = advance tranformation(data, 4)
C:\Users\jiash\AppData\Local\Continuum\anaconda3\lib\site-packages\ipykernel launcher.py:16:
FutureWarning: Sorting because non-concatenation axis is not aligned. A future version
of pandas will change to not sort by default.
To accept the future behavior, pass 'sort=False'.
To retain the current behavior and silence the warning, pass 'sort=True'.
  app.launch new instance()
In [58]:
tr 1.head()
Out[58]:
          fullVisitorId channelGrouping first_ses_from_the_period_start last_ses_from_the_period_end interval_dates unique_date_r
0 0000018966949534117
                      Organic Search
                                                    0 days
                                                                            0 days
                                                                                      167 days
1 0000039738481224681
                             Direct
                                                    0 days
                                                                            0 days
                                                                                      167 days
2 0000073585230191399
                      Organic Search
                                                    0 days
                                                                            0 days
                                                                                      167 days
```

0 days

0 days

167 days

3 0000087588448856385

Organic Search

```
4 0000149787903119437 Organic Search odays fullVisitorid channelGrouping first_ses_from_the_period_start last_ses_from_the_period_end interval_dates unique_date_r
```

)

```
In [92]:
```

```
tr_5 = data[data['date'] >= '2018-05-01']
tr_5.head()
```

Out[92]:

	channelGrouping	date	device.browser	device.deviceCategory	device.isMobile	device.operatingSystem	fullVisitorId	geol
0	Organic Search	2018- 05-11	Chrome	mobile	1	Android	7460955084541987166	
1	Direct	2018- 05-11	Chrome	desktop	0	Macintosh	460252456180441002	S
2	Organic Search	2018- 05-11	Chrome	desktop	0	Chrome OS	3461808543879602873	nc c
3	Direct	2018- 05-11	Chrome	mobile	1	iOS	975129477712150630	
4	Organic Search	2018- 05-11	Internet Explorer	tablet	1	Windows	8381672768065729990	
4								Þ

In [93]:

```
# Build testing dataset
tr 5 = data[data['date'] >= '2018-05-01']
tr 5 maxdate = tr 5['date'].max()
tr_5_mindate = tr_5['date'].min()
df group 5 = pd.DataFrame()
df group 5['channelGrouping'] = tr 5.groupby('fullVisitorId').agg(lambda x: x['channelGrouping'].mo
de()[0])['channelGrouping']
df group 5['first ses from the period start'] = tr 5['date'].min() - tr 5 mindate
df group 5['last ses from the period end'] = tr 5 maxdate - tr 5['date'].max()
df_group_5['interval_dates'] = tr_5['date'].max() - tr_5['date'].min()
df group 5['unique date num'] = len(pd.unique(tr 5['date']))
df_group_5['maxVisitNum'] = tr_5.groupby('fullVisitorId')['totals.visits'].agg("max")
df_group_5['browser'] = tr_5.groupby('fullVisitorId').agg(lambda x: x['device.browser'].mode()[0])[
'device.browser']
df group 5['operatingSystem'] = tr 5.groupby('fullVisitorId').agg(lambda x:
x['device.operatingSystem'].mode()[0])['device.operatingSystem']
df group 5['deviceCategory'] = tr 5.groupby('fullVisitorId').agg(lambda x:
x['device.deviceCategory'].mode()[0])['device.deviceCategory']
df group 5['continent'] = tr 5.groupby('fullVisitorId').agg(lambda x: x['geoNetwork.continent'].mod
e()[0])['geoNetwork.continent']
df group 5['subContinent'] = tr 5.groupby('fullVisitorId').agg(lambda x:
x['qeoNetwork.subContinent'].mode()[0])['qeoNetwork.subContinent']
df group 5['country'] = tr 5.groupby('fullVisitorId').agg(lambda x: x['geoNetwork.country'].mode()[
0])['geoNetwork.country']
df group 5['region'] = tr 5.groupby('fullVisitorId').agg(lambda x: x['geoNetwork.region'].mode()[0]
)['geoNetwork.region']
df_group_5['metro'] = tr_5.groupby('fullVisitorId').agg(lambda x: x['geoNetwork.metro'].mode()[0])[
'geoNetwork.metro']
df group 5['city'] = tr 5.groupby('fullVisitorId').agg(lambda x: x['geoNetwork.city'].mode()[0])['g
eoNetwork.citv'l
df group 5['networkDomain'] = tr 5.groupby('fullVisitorId').agg(lambda x:
  geoNetwork.networkDomain'].mode()[0])['geoNetwork.networkDomain']
df_group_5['source'] = tr_5.groupby('fullVisitorId').agg(lambda x: x['trafficSource.source'].mode()
[0])['trafficSource.source']
df_group_5['medium'] = tr_5.groupby('fullVisitorId').agg(lambda x: x['trafficSource.medium'].mode()
[0])['trafficSource.medium']
df_group_5['isMobile'] = tr_5.groupby('fullVisitorId')['device.isMobile'].agg("sum")
df group 5['bounce sessions'] = tr 5.groupby('fullVisitorId')['totals.bounces'].agg("sum")
df group 5['hits sum'] = tr 5.groupby('fullVisitorId')['totals.hits'].agg("sum")
df_group_5['hits_mean'] = tr_5.groupby('fullVisitorId')['totals.hits'].agg("mean")
df_group_5['pageviews_sum'] = tr_5.groupby('fullVisitorId')['totals.pageviews'].agg("sum")
df group 5['pageviews mean'] = tr 5.groupby('fullVisitorId')['totals.pageviews'].agg("mean")
df_group_5['session_cnt'] = len(tr_5['visitStartTime'])
df group 5['transactionRevenue'] = tr 5.groupby('fullVisitorId')['totals.transactionRevenue'].agg(
"sum")
```

```
df group 5['transactions'] = tr 5.groupby('fullVisitorId')['totals.transactions'].agg("sum")
df group 5['target'] = np.nan
df group 5['return'] = np.nan
In [95]:
tr 5.head()
Out [95]:
   channelGrouping
                    date device.browser device.deviceCategory device.isMobile device.operatingSystem
                                                                                                      fullVisitorId geol
                   2018-
 0
      Organic Search
                                                                                      Android 7460955084541987166
                               Chrome
                                                    mobile
                   05-11
                   2018-
             Direct 2010
05-11
 1
                               Chrome
                                                   desktop
                                                                      0
                                                                                    Macintosh
                                                                                              460252456180441002
                                                                                                                   S
                                                                                   Chrome OS 3461808543879602873
      Organic Search
                               Chrome
                                                   desktop
                   05-11
             Direct 2018-
05-11
 3
                               Chrome
                                                                                         iOS
                                                                                             975129477712150630
                                                    mobile
                                                                      1
                   2018-
                               Internet
                                                                                     Windows 8381672768065729990
      Organic Search
                                                     tablet
                               Explorer
4
In [96]:
train_combined = pd.concat([tr_1, tr_2, tr_3, tr_4, tr_5], sort=False)
In [97]:
train combined.columns
Out[97]:
Index(['fullVisitorId', 'channelGrouping', 'first ses from the period start',
         'last_ses_from_the_period_end', 'interval_dates', 'unique date num',
         'maxVisitNum', 'browser', 'operatingSystem', 'deviceCategory',
        'continent', 'subContinent', 'country', 'region', 'metro', 'city', 'networkDomain', 'source', 'medium', 'isMobile', 'bounce_sessions',
         'hits_sum', 'hits_mean', 'pageviews_sum', 'pageviews_mean',
         'session cnt', 'transactionRevenue', 'transactions', 'ret', 'target',
         'date', 'device.browser', 'device.deviceCategory', 'device.isMobile',
         'device.operatingSystem', 'geoNetwork.city', 'geoNetwork.continent',
        'geoNetwork.country', 'geoNetwork.metro', 'geoNetwork.networkDomain', 'geoNetwork.region', 'geoNetwork.subContinent', 'totals.bounces',
         'totals.hits', 'totals.newVisits', 'totals.pageviews',
         'totals.sessionQualityDim', 'totals.timeOnSite',
         'totals.totalTransactionRevenue', 'totals.transactionRevenue',
         'totals.transactions', 'totals.visits', 'trafficSource.adContent',
         'trafficSource.adwordsClickInfo.adNetworkType',
         'trafficSource.adwordsClickInfo.gclId',
        'trafficSource.adwordsClickInfo.page',
        'trafficSource.adwordsClickInfo.slot', 'trafficSource.campaign',
        'trafficSource.keyword', 'trafficSource.medium',
         'trafficSource.referralPath', 'trafficSource.source', 'visitId',
         'visitNumber', 'visitStartTime'],
       dtype='object')
In [98]:
drop col = ['date', 'device.browser', 'device.deviceCategory', 'device.isMobile',
         'device.operatingSystem', 'geoNetwork.city', 'geoNetwork.continent',
         'geoNetwork.country', 'geoNetwork.metro', 'geoNetwork.networkDomain', 'geoNetwork.region', 'geoNetwork.subContinent', 'totals.bounces',
         'totals.hits', 'totals.newVisits', 'totals.pageviews',
         'totals.sessionQualityDim', 'totals.timeOnSite',
         'totals.totalTransactionRevenue', 'totals.transactionRevenue',
```

'totals.transactions', 'totals.visits', 'trafficSource.adContent',

'trafficSource.adwordsClickInfo.adNetworkType',

'trafficSource.adwordsClickInfo.gclId',

```
crafficource.auworuscffckffffo.page ,
        'trafficSource.adwordsClickInfo.slot', 'trafficSource.campaign',
        'trafficSource.keyword', 'trafficSource.medium',
        'trafficSource.referralPath', 'trafficSource.source', 'visitId',
        'visitNumber', 'visitStartTime']
In [99]:
train combined 2 = train combined.drop(columns=drop col)
In [108]:
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
c = ['city','browser','channelGrouping',"operatingSystem","continent",'subContinent','country',
     'region','metro','networkDomain','source','medium', 'deviceCategory']
for col in c:
    train combined 2[col] = train combined 2[col].fillna('na')
    train combined 2[col] = le.fit transform(train combined 2[col].values)
In [109]:
train combined 2
Out[109]:
                fullVisitorId channelGrouping first_ses_from_the_period_start last_ses_from_the_period_end interval_dates unique_u
     0 0000018966949534117
                                                             0 days
                                                                                       0 days
                                                                                                  167 days
     1 0000039738481224681
                                       2
                                                             0 days
                                                                                       0 days
                                                                                                  167 days
     2 0000073585230191399
                                       4
                                                             0 days
                                                                                       0 days
                                                                                                  167 days
     3 0000087588448856385
                                       4
                                                                                       0 days
                                                                                                  167 days
                                                             0 davs
     4 0000149787903119437
                                       4
                                                             0 days
                                                                                       0 days
                                                                                                  167 days
401584 6701149525099562370
                                                               NaT
                                                                                        NaT
                                                                                                     NaT
401585 6154541330147351453
                                       4
                                                               NaT
                                                                                                     NaT
                                                                                        NaT
401586 6013469762773705448
                                                               NaT
                                                                                        NaT
                                                                                                     NaT
401587 4565378823441900999
                                       4
                                                               NaT
                                                                                        NaT
                                                                                                     NaT
401588 3875690118293601911
                                                               NaT
                                                                                         NaT
                                                                                                     NaT
1099708 rows × 30 columns
In [110]:
train_combined_2['interval_dates'] = pd.to_numeric(train_combined_2['interval_dates'], errors= 'coe
train_combined_2['first_ses_from_the_period_start'] =
pd.to_numeric(train_combined_2['first_ses_from_the_period_start'], errors= 'coerce')
train combined 2['last ses from the period end'] =
pd.to numeric(train combined 2['last ses from the period end'], errors= 'coerce')
In [111]:
train combined 2.head()
Out[111]:
           full V is it or Id channel Grouping \quad first\_ses\_from\_the\_period\_start \quad last\_ses\_from\_the\_period\_end
                                                                                             interval dates unique of
```

0 0000018966949534117 4 0 0 14428800000000000 1 0000039738481224681 2 0 0 14428800000000000 2 0000073585230191399 4 0 14428800000000000 3 0000087588448856385 0 0 14428800000000000 4 000044070700044040

```
144288000000000000
interval_dates unique_c
In [112]:
# Divide train/ test
train = train_combined_2[train_combined_2['target'].isna()]
test = train combined 2[train combined 2['target'].isna() == False]
In [121]:
train.sort_values(by='first_ses_from_the_period_start')
Out[121]:
                fullVisitorId channelGrouping first_ses_from_the_period_start last_ses_from_the_period_end
                                                                                                        interval_dates
     0 7460955084541987166
                                                   -9223372036854775808
                                                                             -9223372036854775808
                                                                                                 9223372036854775808
 133857 9900874527485563945
                                         4
                                                   -9223372036854775808
                                                                             -9223372036854775808
                                                                                                 9223372036854775808
133858 6037578503108830215
                                                   -9223372036854775808
                                                                             -9223372036854775808
                                                                                                 9223372036854775808
 133859 8630812730608319988
                                         4
                                                   -9223372036854775808
                                                                             -9223372036854775808
                                                                                                 9223372036854775808
                                                   -9223372036854775808
                                                                             -9223372036854775808
133860 7827975973225241449
                                                                                                 9223372036854775808
267729 7476629900831012268
                                         6
                                                   -9223372036854775808
                                                                             -9223372036854775808
                                                                                                 9223372036854775808
267730 1184221904466941690
                                         5
                                                   -9223372036854775808
                                                                             -9223372036854775808
                                                                                                  9223372036854775808
267731 7875020615350219520
                                         2
                                                   -9223372036854775808
                                                                             -9223372036854775808
                                                                                                 9223372036854775808
267733 8192330271104386623
                                                   -9223372036854775808
                                                                             -9223372036854775808
                                                                                                  9223372036854775808
401588 3875690118293601911
                                                   -9223372036854775808
                                                                             -9223372036854775808
                                                                                                 9223372036854775808
803178 rows × 30 columns
In [116]:
test.head()
Out[116]:
            fullVisitorId channelGrouping first_ses_from_the_period_start last_ses_from_the_period_end
                                                                                                 interval_dates unique_c
  0000018966949534117
                                                                                             144288000000000000
1 0000039738481224681
                                    2
                                                               0
                                                                                             144288000000000000
2 0000073585230191399
                                                               0
                                                                                             14428800000000000
3 0000087588448856385
                                                                                             144288000000000000
                                    4
                                                               0
  0000149787903119437
                                                                                          0 14428800000000000
In [117]:
train.shape
Out[117]:
(803178, 30)
In [118]:
```

```
test.snape
Out[118]:
  (296530, 30)

In [119]:
  train.to_csv("train_final.csv")

In [120]:
  test.to_csv("test_final.csv")
```

Predictive_randomforest_XGBoost

Import necessary libraries

```
In [1]:
```

```
import pandas as pd
import numpy as np
from sklearn.feature_selection import VarianceThreshold
from sklearn.feature selection import SelectKBest, chi2
from sklearn import preprocessing
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn import tree
from sklearn.tree import DecisionTreeRegressor
from sklearn.tree import export_graphviz
from sklearn import metrics
from sklearn.metrics import classification_report, mean_squared_error
from sklearn import linear_model
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn import neighbors
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import classification_report
from sklearn import svm
from sklearn.svm import SVR
from sklearn.model selection import GridSearchCV, RandomizedSearchCV
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
import warnings
warnings.filterwarnings('ignore')
```

In [14]:

```
# All training data
df = pd.read_csv(r'C:\Users\ACER\Desktop\UMN\Predictive
Analysis\FinalProject\data\train_final.csv')
len(df)
df.head(5)
```

Out[14]:

	Unnamed: 0	fullVisitorId	channelGrouping	first_ses_from_the_period_start	last_ses_from_the_period_end	interval_dates ι	unique
0	1	10278554503158	Organic Search	80	87	0	
1	2	20424342248747	Organic Search	121	46	0	
2	3	5103959234087	Organic Search	20	147	0	
3	4	93957001069502	Organic Search	57	110	0	
4	5	114156543135683	Social	7	160	0	

df test

Out[18]	Out[18]:						
	Unnamed: 0	fullVisitorId	channelGrouping	first_ses_from_the_period_start	last_ses_from_the_period_end	interval_date	
0	1417576	18966949534117	Organic Search	104	63		
1	1417577	39738481224681	Direct	43	124		
2	1417578	73585230191399	Organic Search	33	134		
3	1417579	87588448856385	Organic Search	36	131		
4	1417580	149787903119437	Organic Search	20	147		
296525	1714101	9999862054614696520	Organic Search	7	160		
296526	1714102	9999898168621645223	Organic Search	67	100		
296527	1714103	999990167740728398	Direct	93	74		
296528	1714104	9999915620249883537	Organic Search	46	121		
296529	1714105	9999947552481876143	Organic Search	108	59		
296530 rd	ows × 41 c	columns					
4						Þ	
In [19]:							
df_test	<pre>df_test = df_test.drop(columns = ['isVideoAd_mean',</pre>						
	'hits_median',						

In [20]:

In [21]:

```
x_train_return = df.drop(['fullVisitorId','target','ret'], axis = 1)
y_train_return = df['ret']

x_train_target = df[df['ret'] == 1].drop(['fullVisitorId','target','ret'], axis = 1)
y_train_target = df[df['ret'] == 1]['target']

x_test = df_test.drop(['fullVisitorId','target','ret'], axis = 1)
```

In [22]:

```
x_test.info()
```

'hits_sd',
'pageviews_min',
'pageviews_max',
'pageviews_median',
'pageviews_sd'])

```
browser
                                   296530 non-null int32
                                   296530 non-null int32
operatingSystem
                                   296530 non-null int32
deviceCategory
continent
                                   296530 non-null int32
subContinent
                                   296530 non-null int32
                                   296530 non-null int32
country
                                   296530 non-null int32
region
                                   296530 non-null int32
metro
                                   296530 non-null int32
city
                                   296530 non-null int32
networkDomain
source
                                   296530 non-null int32
medium
                                   296530 non-null int32
isMobile
                                   296530 non-null float64
bounce sessions
                                   296530 non-null int64
hits sum
                                   296530 non-null int64
                                   296530 non-null float64
hits mean
pageviews sum
                                   296530 non-null int64
                                   296520 non-null float64
pageviews_mean
                                   296530 non-null int64
session cnt
transactionRevenue
                                   296530 non-null float64
                                   296530 non-null int64
transactions
dtypes: float64(4), int32(13), int64(10)
memory usage: 46.4 MB
```

In [23]:

```
# Split train and validation data
# for target variable = return
x_train_return, x_valid_return, y_train_return, y_valid_return = train_test_split(x_train_return, y
_train_return, test_size=0.33)
# for target variable = target
x_train_target, x_valid_target, y_train_target, y_valid_target = train_test_split(x_train_target, y
_train_target, test_size=0.33)
```

In [676]:

```
# Normalized training dataset
# Normalize train_target
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(x_train_target)
x train target scaled = scaler.transform(x train target)
x_valid_target_scaled = scaler.transform(x_valid_target)
# Normalize train return
scaler = MinMaxScaler()
scaler.fit(x train return)
x train return scaled = scaler.transform(x train return)
x valid_return_scaled = scaler.transform(x_valid_return)
# Normalize test dataset
scaler = MinMaxScaler()
scaler.fit(x test)
x_test_scaled = scaler.transform(x_test)
```

In [677]:

```
# Deal with nan values
np.argwhere(np.isnan(x_train_return_scaled))
x_train_return_scaled = np.nan_to_num(x_train_return_scaled)

np.argwhere(np.isnan(x_valid_return_scaled))
x_valid_return_scaled = np.nan_to_num(x_valid_return_scaled)

np.argwhere(np.isnan(x_test_scaled))
x_test_scaled = np.nan_to_num(x_test_scaled)
```

Model 1: Random Forest

Using original features to see the model performance

```
In [678]:
```

```
# Download necessary library for random forest regressor

from sklearn.ensemble import RandomForestClassifier

from sklearn.ensemble import RandomForestClassifier
```

In [680]:

```
# Build random forest classification model
clf = RandomForestClassifier(n_estimators=100, max_depth=3, random_state=0)
clf.fit(x_train_return_scaled, y_train_return)
```

Out[680]:

In [679]:

```
# Build random forest regression model
reg = RandomForestRegressor(max_depth=10, n_estimators=100)
reg.fit(x_train_target_scaled, y_train_target)
```

Out[679]:

In [682]:

```
# Classification Report
y_pred_valid_return = clf.predict(x_valid_return_scaled)
print(classification_report(y_valid_return, y_pred_valid_return))
# Calculating R-square
print("Its R-square of random forest regression model is", reg.score(x_train_target_scaled, y_train_target))
```

	precision	recall	f1-score	support
0	0.99	1.00	1.00	464923 2877
accuracy macro avg	0.50	0.50	0.99	467800 467800
weighted avg	0.99	0.99	0.99	467800

Its R-square of random forest regression model is 0.4786546091953813

In [683]:

```
# Calculating RMSE before tuning hyperparameters
y_pred_target = reg.predict(x_valid_target_scaled)
print("The RMSE of random forest regression model is",np.sqrt(mean_squared_error(y_valid_target, y _pred_target)))
```

Its RMSE of random forest regression model is 4.00323956489714

Utilizing randomizedsearchCV to tune hyperparameters

In [684]:

```
from sklearn.model selection import RandomizedSearchCV
# Number of trees in random forest
n estimators = [int(x) for x in np.linspace(start = 200, stop = 500, num = 10)]
# Number of features to consider at every split
max features = ['auto', 'sqrt']
# Maximum number of levels in tree
max depth = [int(x) for x in np.linspace(10, 100, num = 11)]
max depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10]
# Minimum number of samples required at each leaf node
min samples leaf = [1, 2, 4]
# Method of selecting samples for training each tree
bootstrap = [True, False]
# Create the random grid
random grid = {'n estimators': n estimators,
               'max features': max features,
               'max depth': max depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}
print(random grid)
{'n estimators': [200, 233, 266, 300, 333, 366, 400, 433, 466, 500], 'max features': ['auto',
'sqrt'], 'max depth': [10, 19, 28, 37, 46, 55, 64, 73, 82, 91, 100, None], 'min samples split': [2
, 5, 10], 'min samples leaf': [1, 2, 4], 'bootstrap': [True, False]}
In [685]:
# Use RandomizedSearchCV for best hyperparameters
# First create the base model to tune
reg2 = RandomForestRegressor()
# Random search of parameters, using 3 fold cross validation,
# search across 100 different combinations, and use all available cores
reg2 random = RandomizedSearchCV(estimator = reg2, param distributions = random grid, n iter = 10,
cv = 3, verbose=2, random state=42, n jobs = -1)
# Fit the random search model
reg2 random.fit(x train target scaled, y train target)
Fitting 3 folds for each of 10 candidates, totalling 30 fits
[Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done 30 out of 30 | elapsed: 1.2min finished
Out[685]:
RandomizedSearchCV(cv=3, error score='raise-deprecating',
                   estimator=RandomForestRegressor(bootstrap=True,
                                                   criterion='mse',
                                                   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='warn',
                                                   n jobs=None, oob score=False,
                                                   random sta...
                   iid='warn', n_iter=10, n_jobs=-1,
                                                     rm..... m-1--1
```

```
'max_depth': [10, 19, 28, 37, 46, 55,
                                                        64, 73, 82, 91, 100,
                                                        None],
                                         'max_features': ['auto', 'sqrt'],
                                         'min_samples_leaf': [1, 2, 4],
                                         'min_samples_split': [2, 5, 10],
                                          'n_estimators': [200, 233, 266, 300, 333, 366, 400, 433,
                                                           466, 500]},
                   pre dispatch='2*n jobs', random state=42, refit=True,
                   return train score=False, scoring=None, verbose=2)
In [686]:
reg2 random.best params
Out[686]:
{'n estimators': 200,
 'min_samples_split': 5,
 'min_samples_leaf': 2,
 'max features': 'sqrt',
 'max depth': 10,
 'bootstrap': True}
In [687]:
best random = RandomForestRegressor(n estimators=200,
                                  min samples split=5,
                                  min samples leaf=2,
                                  max features='sqrt',
                                  max depth=10,
                                  bootstrap=True)
best random.fit(x train target scaled, y train target)
y_predF = best_random.predict(x_valid_target_scaled)
print("Its RMSE of tuned random forest model is",np.sqrt(mean_squared_error(y_valid_target,
y predF)))
Its RMSE of tuned random forest model is 3.901847198007343
In [688]:
y pred target = best random.predict(x test scaled)
y_pred_target
Out[6881:
array([0.28238238, 0.3591359 , 0.02736908, ..., 0.25784802, 0.36411663,
       0.37251495])
In [689]:
df test1 = pd.read csv(r'C:\Users\ACER\Desktop\UMN\Predictive Analysis\FinalProject\data\test.csv'
,converters={'fullVisitorId': lambda x: str(x)})
In [691]:
#test
data = {'fullVisitorId': [i for i in df test1.fullVisitorId], 'PredictedLogRevenue': [j for j in y
pred_target] }
submission_random_forest = pd.DataFrame(data)
submission random forest
Out[691]:
```

param_distributions={'pootstrap': [True, Faise],

fullVisitorId PredictedLogRevenue

1	000003973 84647234681	PredictedLogRevende
2	0000073585230191399	0.027369
3	0000087588448856385	0.037537
4	0000149787903119437	0.004584
•••		
296525	9999862054614696520	0.964398
296526	9999898168621645223	0.036835
296527	999990167740728398	0.257848
296528	9999915620249883537	0.364117
296529	9999947552481876143	0.372515

296530 rows × 2 columns

```
In [692]:
```

```
import csv
submission_random_forest.to_csv(r'C:\Users\ACER\Desktop\UMN\Predictive
Analysis\FinalProject\data\submission_random_forest.csv', index = False)
```

Utilizing feature selection and executing random forest model with tuned hyperparameters

In [693]:

In [694]:

```
feature_importances_clf
```

Out[694]:

	importance
interval_dates	0.285881
maxVisitNum	0.186963
unique_date_num	0.154433
last_ses_from_the_period_end	0.144428
session_cnt	0.072903
pageviews_sum	0.041733
hits_sum	0.025367
first_ses_from_the_period_start	0.025121
bounce_sessions	0.015758
pageviews_mean	0.008133
hits_mean	0.007734
country	0.007131
transactionRevenue	0.004848
source	0.004131
medium	0.003448
transactions	0.002705
region	0.002504
deviceCategory	0.001740
operatingSystem	0.001393
channelGrouping	0.001089

```
        networkDomain
        importance 0.000966

        city
        0.000576

        metro
        0.000378

        subContinent
        0.000355

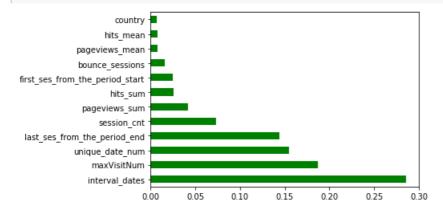
        isMobile
        0.000250

        browser
        0.000030

        continent
        0.000000
```

In [695]:

```
#plot graph of feature importances for better visualization
import matplotlib.pyplot as plt
feature_importances_clf2 = pd.Series(clf.feature_importances_, index=x_train_target.columns)
feature_importances_clf2.nlargest(12).plot(kind='barh',color='g')
plt.show()
```



In [697]:

```
feature_importances_clf[feature_importances_clf['importance']>= 0.05].index.tolist()
```

Out[697]:

```
['interval_dates',
  'maxVisitNum',
  'unique_date_num',
  'last_ses_from_the_period_end',
  'session_cnt']
```

In [698]:

In [699]:

```
feature_importances_reg
```

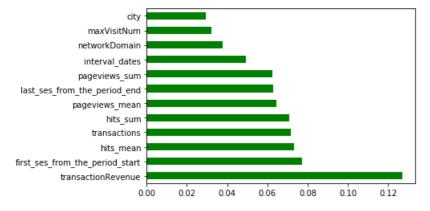
Out[699]:

	importance
transactionRevenue	0.127108
first_ses_from_the_period_start	0.077094
hits_mean	0.073249
transactions	0.071604
hits_sum	0.070696

last_ses_from_the_period_end 0.063047 pageviews_sum 0.062329 interval_dates 0.049413 networkDomain 0.037815 maxVisitNum 0.032151 city 0.029512 session_cnt 0.026894 unique_date_num 0.025497 region 0.024016 operatingSystem 0.023880 metro 0.022023 channelGrouping 0.021965 bounce_sessions 0.018272 country 0.017622 source 0.014289 medium 0.013169 continent 0.007856 browser 0.006161 deviceCategory 0.005272 isMobile 0.005216	pageviews_mean	importance
interval_dates	last_ses_from_the_period_end	0.063047
networkDomain 0.037815 maxVisitNum 0.032151 city 0.029512 session_cnt 0.026894 unique_date_num 0.025497 region 0.024016 operatingSystem 0.023880 metro 0.022023 channelGrouping 0.021965 bounce_sessions 0.018272 country 0.017622 source 0.014289 medium 0.013169 continent 0.009252 subContinent 0.007856 browser 0.006161 deviceCategory 0.005272	pageviews_sum	0.062329
maxVisitNum 0.032151 city 0.029512 session_cnt 0.026894 unique_date_num 0.025497 region 0.024016 operatingSystem 0.023880 metro 0.022023 channelGrouping 0.021965 bounce_sessions 0.018272 country 0.017622 source 0.014289 medium 0.013169 continent 0.007856 browser 0.006161 deviceCategory 0.005272	interval_dates	0.049413
city 0.029512 session_cnt 0.026894 unique_date_num 0.025497 region 0.024016 operatingSystem 0.023880 metro 0.022023 channelGrouping 0.021965 bounce_sessions 0.018272 country 0.017622 source 0.014289 medium 0.013169 continent 0.009252 subContinent 0.007856 browser 0.006161 deviceCategory 0.005272	networkDomain	0.037815
session_cnt 0.026894 unique_date_num 0.025497 region 0.024016 operatingSystem 0.023880 metro 0.022023 channelGrouping 0.021965 bounce_sessions 0.018272 country 0.017622 source 0.014289 medium 0.013169 continent 0.007856 browser 0.006161 deviceCategory 0.005272	maxVisitNum	0.032151
unique_date_num	city	0.029512
region 0.024016 operatingSystem 0.023880 metro 0.022023 channelGrouping 0.021965 bounce_sessions 0.018272 country 0.017622 source 0.014289 medium 0.013169 continent 0.009252 subContinent 0.007856 browser 0.006161 deviceCategory 0.005272	session_cnt	0.026894
operatingSystem 0.023880 metro 0.022023 channelGrouping 0.021965 bounce_sessions 0.018272 country 0.017622 source 0.014289 medium 0.013169 continent 0.009252 subContinent 0.007856 browser 0.006161 deviceCategory 0.005272	unique_date_num	0.025497
metro 0.022023 channelGrouping 0.021965 bounce_sessions 0.018272 country 0.017622 source 0.014289 medium 0.013169 continent 0.009252 subContinent 0.007856 browser 0.006161 deviceCategory 0.005272	region	0.024016
channelGrouping 0.021965 bounce_sessions 0.018272 country 0.017622 source 0.014289 medium 0.013169 continent 0.009252 subContinent 0.007856 browser 0.006161 deviceCategory 0.005272	operatingSystem	0.023880
bounce_sessions 0.018272 country 0.017622 source 0.014289 medium 0.013169 continent 0.009252 subContinent 0.007856 browser 0.006161 deviceCategory 0.005272	metro	0.022023
country 0.017622 source 0.014289 medium 0.013169 continent 0.009252 subContinent 0.007856 browser 0.006161 deviceCategory 0.005272	channelGrouping	0.021965
source 0.014289 medium 0.013169 continent 0.009252 subContinent 0.007856 browser 0.006161 deviceCategory 0.005272	bounce_sessions	0.018272
medium 0.013169 continent 0.009252 subContinent 0.007856 browser 0.006161 deviceCategory 0.005272	country	0.017622
continent 0.009252 subContinent 0.007856 browser 0.006161 deviceCategory 0.005272	source	0.014289
subContinent 0.007856 browser 0.006161 deviceCategory 0.005272	medium	0.013169
browser 0.006161 deviceCategory 0.005272	continent	0.009252
deviceCategory 0.005272	subContinent	0.007856
	browser	0.006161
isMobile 0.005216	deviceCategory	0.005272
	isMobile	0.005216

In [700]:

```
#plot graph of feature importances for better visualization
import matplotlib.pyplot as plt
feature_importances_reg2 = pd.Series(best_random.feature_importances_, index=x_train_target.columns)
feature_importances_reg2.nlargest(12).plot(kind='barh',color='g')
plt.show()
```



In [701]:

```
feature_importances_reg[feature_importances_reg['importance']>= 0.05].index.tolist()
```

Out[701]:

```
['transactionRevenue',
  'first_ses_from_the_period_start',
  'hits_mean',
  'transactions',
  'hits_sum',
  'pageviews_mean',
  'last_ses_from_the_period_end',
  'pageviews sum']
```

In [713]:

```
# Split train and validation data

# for target variable = return
x_train_return, x_valid_return, y_train_return, y_valid_return = train_test_split(x_train_return, y
_train_return, test_size=0.33)

# for target variable = target
x_train_target, x_valid_target, y_train_target, y_valid_target = train_test_split(x_train_target, y
_train_target, test_size=0.33)
```

In [714]:

```
# Select important features
x train return = x train return[['interval dates',
                                  'maxVisitNum',
                                  'unique_date_num',
                                  'last_ses_from_the_period_end',
                                  'session cnt']]
x_valid_return = x_valid_return[['interval_dates',
                                  'maxVisitNum',
                                  'unique date num',
                                  'last_ses_from_the_period_end',
                                  'session cnt']]
x train target = x train target[['transactionRevenue',
                                  'first_ses_from_the_period_start',
                                  'hits mean',
                                  'transactions',
                                  'hits_sum',
                                  'pageviews mean',
                                  'last_ses_from_the_period_end',
                                  'pageviews_sum']]
x_valid_target = x_valid_target[['transactionRevenue',
                                  'first_ses_from_the_period_start',
                                  'hits mean',
                                  'transactions',
                                  'hits_sum',
                                  'pageviews_mean',
                                  'last ses from the period end',
                                  'pageviews_sum']]
x_test_return = x_test[['interval dates',
                                  'maxVisitNum',
                                  'unique_date_num',
                                  'last ses from the period end',
                                  'session_cnt']]
x test target = x test[['transactionRevenue',
                                  'first_ses_from_the_period_start',
                                  'hits mean',
                                  'transactions',
                                  'hits_sum',
                                  'pageviews mean',
                                  'last_ses_from_the_period_end',
                                  'pageviews_sum']]
```

In [716]:

```
# Normalize train_target
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(x_train_target)
x_train_target_scaled = scaler.transform(x_train_target)
x_valid_target_scaled = scaler.transform(x_valid_target)

# Normalize train_return
scaler = MinMaxScaler()
scaler.fit(x_train_return)
x_train_return_scaled = scaler.transform(x_train_return)
x_valid_return_scaled = scaler.transform(x_valid_return)

# Normalize test

Normalize test
```

```
scaler = MinMaxScaler()
scaler.fit(x_test_return)
x_test_return_scaled = scaler.transform(x_test_return)
scaler.fit(x_test_target)
x_test_target_scaled = scaler.transform(x_test_target)
```

In [717]:

```
# Dealing with NAN value
np.argwhere(np.isnan(x_train_return_scaled))
x_train_return_scaled = np.nan_to_num(x_train_return_scaled)

np.argwhere(np.isnan(x_valid_return_scaled))
x_valid_return_scaled = np.nan_to_num(x_valid_return_scaled)

np.argwhere(np.isnan(x_test_scaled))
x_test_return_scaled = np.nan_to_num(x_test_return_scaled)
x_test_target_scaled = np.nan_to_num(x_test_target_scaled)
```

In [718]:

```
# Build random forest model
# For classification model (target variable = return)
clf = RandomForestClassifier(n_estimators=100, max_depth=3, random_state=0)
clf.fit(x_train_return_scaled, y_train_return)
```

Out[718]:

In [719]:

```
y_pred_valid_return = clf.predict(x_valid_return_scaled)
# Classification Report
print(classification_report(y_valid_return, y_pred_valid_return))
# For regression model (target variable = target)
reg = RandomForestRegressor(max_depth=10, n_estimators=100)
reg.fit(x_train_target_scaled, y_train_target)
```

	precision	recall	f1-score	support
0 1	0.99 0.60	1.00	1.00 0.02	93699 568
accuracy macro avg	0.80	0.51	0.99 0.51	94267 94267
weighted avg	0.99	0.99	0.99	94267

Out[719]:

In [720]:

```
# Calculating R-square
print("Its R-square of random forest regression model is", reg.score(x_train_target_scaled,
y_train_target))
```

```
Its R-square of random forest regression model is 0.722565384969677
```

```
In [721]:
```

```
best_random.fit(x_train_target_scaled, y_train_target)
y_predF_new = best_random.predict(x_valid_target_scaled)
print("Its RMSE of tuned random forest model is",np.sqrt(mean_squared_error(y_valid_target,
y_predF_new)))
```

Its RMSE of tuned random forest model is 3.474077726323697

In [722]:

```
y_pred_target_new = best_random.predict(x_test_target_scaled)
y_pred_target_new
```

Out[722]:

```
array([0.16788353, 0.16438741, 0.16438741, ..., 0.36746037, 0.25762755, 0.53529752])
```

In [723]:

```
df_test1 = pd.read_csv(r'C:\Users\ACER\Desktop\UMN\Predictive Analysis\FinalProject\data\test.csv'
,converters={'fullVisitorId': lambda x: str(x)})
```

In [724]:

```
#test
data_random_forest = {'fullVisitorId': [i for i in df_test1.fullVisitorId], 'PredictedLogRevenue':
[j for j in y_pred_target_new]}
submission_random_forest_new = pd.DataFrame(data)
submission_random_forest_new
```

Out[724]:

fullVisitorId PredictedLogRevenue

0	0000018966949534117	0.282382
1	0000039738481224681	0.359136
2	0000073585230191399	0.027369
3	0000087588448856385	0.037537
4	0000149787903119437	0.004584
•••		
296525	9999862054614696520	0.964398
296526	9999898168621645223	0.036835
296527	999990167740728398	0.257848
296528	9999915620249883537	0.364117
296529	9999947552481876143	0.372515

296530 rows × 2 columns

In [725]:

```
submission_random_forest_new.to_csv(r'C:\Users\ACER\Desktop\UMN\Predictive
Analysis\FinalProject\data\submission_random_forest2.csv', index = False)
```

Model 2: XGboost

```
In [726]:
```

```
# Import necessary libraries
from sklearn import ensemble
import xgboost as xgb
from sklearn.utils import shuffle
from sklearn.metrics import mean_squared_error
```

In [727]:

```
x_train_return = df.drop(['fullVisitorId','target','ret'], axis = 1)
y_train_return = df['ret']

x_train_target = df[df['ret'] == 1].drop(['fullVisitorId','target','ret'], axis = 1)
y_train_target = df[df['ret'] == 1]['target']

x_test = df_test.drop(['fullVisitorId','target','ret'], axis = 1)
```

In [728]:

```
# Split train and validation data

# for target variable = return
x_train_return, x_valid_return, y_train_return, y_valid_return = train_test_split(x_train_return, y
_train_return, test_size=0.33)

# for target variable = target
x_train_target, x_valid_target, y_train_target, y_valid_target = train_test_split(x_train_target, y
_train_target, test_size=0.33)
```

In [729]:

```
# Normalized training & testing dataset
# Normalize train target
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(x train target)
x train target scaled = scaler.transform(x train target)
x valid target scaled = scaler.transform(x valid target)
# Normalize train_return
scaler = MinMaxScaler()
scaler.fit(x train return)
x_train_return_scaled = scaler.transform(x_train_return)
x_valid_return_scaled = scaler.transform(x_valid_return)
# Normalize test
scaler = MinMaxScaler()
scaler.fit(x test)
x test scaled = scaler.transform(x test)
```

In [730]:

```
# Dealing with NAN value
np.argwhere(np.isnan(x_train_return_scaled))
x_train_return_scaled = np.nan_to_num(x_train_return_scaled)

np.argwhere(np.isnan(x_valid_return_scaled))
x_valid_return_scaled = np.nan_to_num(x_valid_return_scaled)

np.argwhere(np.isnan(x_test_scaled))
x_test_scaled = np.nan_to_num(x_test_scaled)
```

In [731]:

```
max delta step=0,
                           subsample=1,
                           colsample bytree=1,
                           colsample_bylevel=1,
                           reg alpha=0,
                           reg lambda=0,
                           scale pos weight=1,
                           seed=1,
                           missing=None)
clf.fit(x_train_return_scaled, y_train_return, eval_metric='auc', verbose=True,
            eval set=[(x valid return scaled, y valid return)], early stopping rounds=5)
y pred valid return = clf.predict(x valid return scaled)
[0] validation 0-auc:0.840764
Will train until validation 0-auc hasn't improved in 5 rounds.
[1] validation 0-auc:0.867023
[2] validation 0-auc:0.876627
[3] validation 0-auc:0.877874
[4] validation 0-auc:0.877972
[5] validation_0-auc:0.879299
[6] validation_0-auc:0.879304
[7] validation 0-auc:0.880145
[8] validation_0-auc:0.881351
[9] validation 0-auc:0.883728
[10] validation_0-auc:0.884225
[11] validation_0-auc:0.884786
[12] validation 0-auc:0.884822
[13] validation_0-auc:0.884727
[14] validation 0-auc:0.884264
[15] validation 0-auc:0.884703
[16] validation_0-auc:0.884399
[17] validation 0-auc:0.884525
Stopping. Best iteration:
[12] validation_0-auc:0.884822
In [732]:
# CLassification Report
print(classification_report(y_valid_return, y_pred_valid_return))
             precision recall f1-score support
                                    1.00
          0
                  0.99
                           1.00
                                             464957
                  0.43
                           0.02
                                     0.04
          1
                                               2843
                                      0.99
                                              467800
   accuracy
                        0.51
  macro avq
                  0.71
                                  0.99
                                              467800
weighted avg
                  0.99
                            0.99
                                              467800
In [754]:
# XGboost Regression
xg_reg = xgb.XGBRegressor(learning_rate=0.1,max_depth=10)
In [755]:
# fit the model with the training data
xg_reg.fit(x_train_target_scaled, y_train_target)
[21:20:52] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
```

Out[755]:

XGBRegressor(base score=0.5, booster='gbtree', colsample bylevel=1,

colsample bynode=1, colsample bytree=1, gamma=0,

importance_type='gain', learning_rate=0.1, max_delta_step=0,

```
max_deptn=10, min_cniid_weignt=1, missing=None, n_estimators=100,
n_jobs=1, nthread=None, objective='reg:linear', random_state=0,
reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
silent=None, subsample=1, verbosity=1)
```

In [756]:

```
# Calculating R-square
print("Its R-square of XGboost regression model is", xg_reg.score(x_train_target_scaled,
y_train_target))
# Calculating RMSE for regression
y_pred_valid_target = xg_reg.predict(x_valid_target_scaled)
print("Its RMSE of XGboost regression model is",np.sqrt(mean_squared_error(y_pred_valid_target, y_valid_target)))
```

Its R-square of XGboost regression model is 0.9468226969141958 Its RMSE of XGboost regression model is 4.407437111752069

In [757]:

```
y_pred = xg_reg.predict(x_test_scaled)
```

In [758]:

```
y_pred
```

Out[758]:

```
array([ 0.4664757 , 4.687464 , 0.06096366, ..., 0.00505006, 0.02956718, -0.2237975 ], dtype=float32)
```

In [759]:

```
df_test1 = pd.read_csv(r'C:\Users\ACER\Desktop\UMN\Predictive Analysis\FinalProject\data\test.csv'
,converters={'fullVisitorId': lambda x: str(x)})
```

In [760]:

```
data_xgboost = {'fullVisitorId': [i for i in df_test1.fullVisitorId], 'PredictedLogRevenue': [j for j in y_pred]}
submission_xgboost = pd.DataFrame(data_xgboost)
submission_xgboost
```

Out[760]:

fullVisitorId PredictedLogRevenue

0	0000018966949534117	0.466476
1	0000039738481224681	4.687464
2	0000073585230191399	0.060964
3	0000087588448856385	-0.021676
4	0000149787903119437	0.437586
296525	9999862054614696520	1.720398
296526	9999898168621645223	-0.039090
296527	999990167740728398	0.005050
296528	9999915620249883537	0.029567
296529	9999947552481876143	-0.223798

296530 rows × 2 columns

In [761]:

```
submission xgboost.to csv(r'C:\Users\ACER\Desktop\UMN\Predictive
Analysis\FinalProject\data\submission xgboost.csv', index = False)
In [762]:
submission_xgboost
Out[762]:
                fullVisitorId PredictedLogRevenue
     0 0000018966949534117
                                      0.466476
     1 0000039738481224681
                                      4.687464
     2 0000073585230191399
                                      0.060964
     3 0000087588448856385
                                      -0.021676
     4 0000149787903119437
                                      0.437586
 296525 9999862054614696520
                                      1.720398
 296526 9999898168621645223
                                      -0.039090
        999990167740728398
                                      0.005050
 296527
 296528 9999915620249883537
                                      0.029567
 296529 9999947552481876143
                                      -0.223798
296530 rows × 2 columns
```

Utilizing feature selection and executing XGboost model again

In [746]:

In [747]:

```
feature_importances_xg_clf
```

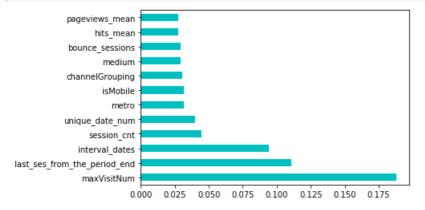
Out[747]:

importanc				
maxVisitNum 0.18				
last_ses_from_the_period_end	0.110923			
interval_dates	0.094427			
session_cnt	0.044560			
unique_date_num	0.039723			
metro 0.031840 isMobile 0.031498				
		channelGrouping	0.030286	
medium	0.029387			
bounce_sessions 0.0291 hits_mean 0.0277				
		pageviews_mean	0.027500	
hits_sum 0.026	0.026518			
region 0.026				
pageviews_sum	0.025819			

source	impontanee		
transactionRevenue	transactionRevenue 0.023313		
city	0.022876		
first_ses_from_the_period_start	0.022041		
networkDomain 0.0201			
operatingSystem 0.0199			
country	country 0.019692		
transactions	ons 0.019419		
subContinent	subContinent 0.018837		
deviceCategory 0.0182			
browser 0.0157			
continent	0.012458		

In [748]:

```
#plot graph of feature importances for better visualization
import matplotlib.pyplot as plt
feature_importances_xg_clf2 = pd.Series(clf.feature_importances_, index=x_train_target.columns)
feature_importances_xg_clf2.nlargest(12).plot(kind='barh',color='c')
plt.show()
```



In [749]:

```
# classification
feature_importances_xg_clf[feature_importances_xg_clf['importance']>= 0.035].index.tolist()
```

Out[749]:

```
['maxVisitNum',
  'last_ses_from_the_period_end',
  'interval_dates',
  'session_cnt',
  'unique_date_num']
```

In [767]:

In [764]:

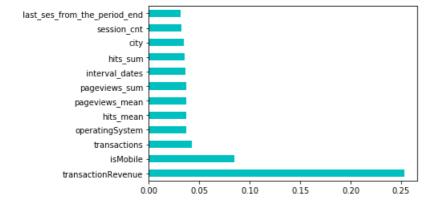
```
feature_importances_xg_reg
```

Out[764]:

transactionRevenue	im p @ \$ 3¤6₹		
isMobile	0.085102		
transactions	0.042302		
operatingSystem	0.037384		
hits_mean	0.037252		
pageviews_mean	0.037240		
pageviews_sum	0.036746		
interval_dates	0.036145		
hits_sum	0.035135		
city	0.034437		
session_cnt	0.032452		
last_ses_from_the_period_end	0.031687		
bounce_sessions	0.031650		
metro	0.029143		
region	0.026959		
medium	0.026599		
first_ses_from_the_period_start	0.025814		
source	0.024834		
unique_date_num	0.024397		
maxVisitNum	0.023539		
networkDomain	0.023277		
country	0.019102		
channelGrouping	0.014901		
browser	0.011254		
continent	0.009093		
deviceCategory	0.006758		
subContinent	0.003363		

In [765]:

```
#plot graph of feature importances for better visualization
import matplotlib.pyplot as plt
feature_importances_xg_reg = pd.Series(xg_reg.feature_importances_, index=x_train_target.columns)
feature_importances_xg_reg.nlargest(12).plot(kind='barh',color='c')
plt.show()
```



In [768]:

```
# regression
feature_importances_xg_reg[feature_importances_xg_reg['importance']>= 0.035].index.tolist()
```

Out[768]:

```
['transactionRevenue',
```

```
'isMobile',
 'transactions',
 'operatingSystem',
 'hits mean',
 'pageviews_mean',
 'pageviews_sum',
 'interval_dates',
 'hits_sum']
In [769]:
# Split train and validation data
# for target variable = return
x_train_return, x_valid_return, y_train_return, y_valid_return = train_test_split(x_train_return, y
_train_return, test_size=0.33)
# for target variable = target
x_train_target, x_valid_target, y_train_target, y_valid_target = train_test_split(x_train_target, y
_train_target, test_size=0.33)
In [770]:
```

```
# Select important features for classification
x_train_return = x_train_return[['maxVisitNum',
                                  'last_ses_from_the_period_end',
                                  'interval dates',
                                  'session_cnt',
                                  'unique_date_num']]
x valid return = x valid return[['maxVisitNum',
                                  'last_ses_from_the_period_end',
                                  'interval dates',
                                  'session cnt',
                                  'unique_date_num']]
x test return = x test[['maxVisitNum',
                                  'last_ses_from_the_period_end',
                                  'interval dates',
                                  'session_cnt',
                                  'unique_date_num']]
# Select important features for regression
x train target = x train target[['transactionRevenue',
                                  'isMobile',
                                  'transactions',
                                  'operatingSystem',
                                  'hits_mean',
                                  'pageviews mean',
                                  'pageviews_sum',
                                  'interval dates',
                                  'hits sum']]
x_valid_target = x_valid_target[['transactionRevenue',
                                  'isMobile',
                                  'transactions',
                                  'operatingSystem',
                                  'hits_mean',
                                  'pageviews_mean',
                                  'pageviews_sum',
                                  'interval dates',
                                  'hits_sum']]
x test target = x test[['transactionRevenue',
                                  'isMobile',
                                  'transactions',
                                  'operatingSystem',
                                  'hits_mean',
                                  'pageviews_mean',
                                  'pageviews_sum',
                                  'interval_dates',
                                  'hits sum']]
```

In [771]:

```
# Normalized training & testing dataset

# Normalize train_target
from sklearn.preprocessing import MinMaxScaler
```

```
scaler = MinMaxScaler()
scaler.fit(x_train_target)
x_train_target_scaled = scaler.transform(x_train_target)
x_valid_target_scaled = scaler.transform(x_valid_target)

# Normalize train_return
scaler = MinMaxScaler()
scaler.fit(x_train_return)
x_train_return_scaled = scaler.transform(x_train_return)
x_valid_return_scaled = scaler.transform(x_valid_return)

# Normalize test
scaler = MinMaxScaler()
scaler.fit(x_test_target)
x_test_target_scaled = scaler.transform(x_test_target)
scaler.fit(x_test_return)
x_test_return_scaled = scaler.transform(x_test_return)
```

In [772]:

```
# Dealing with NAN value
np.argwhere(np.isnan(x_train_return_scaled))
x_train_return_scaled = np.nan_to_num(x_train_return_scaled)
np.argwhere(np.isnan(x_valid_return_scaled))
x_valid_return_scaled = np.nan_to_num(x_valid_return_scaled)
np.argwhere(np.isnan(x_test_scaled))
x_test_return_scaled = np.nan_to_num(x_test_return_scaled)
x_test_target_scaled = np.nan_to_num(x_test_target_scaled)
```

In [773]:

```
# XGboost classification
clf = xgb.XGBClassifier(max depth=10,
                           min_child_weight=1,
                           learning rate=0.1,
                           n estimators=500,
                           silent=True,
                           objective='binary:logistic',
                           gamma=0,
                           max delta_step=0,
                           subsample=1,
                           colsample bytree=1,
                           colsample bylevel=1,
                           reg alpha=0,
                           reg_lambda=0,
                           scale_pos_weight=1,
                           seed=1,
                           missing=None)
clf.fit(x_train_return_scaled, y_train_return, eval_metric='auc', verbose=True,
            eval_set=[(x_valid_return_scaled, y_valid_return)], early_stopping_rounds=5)
y pred valid return = clf.predict(x valid return scaled)
[0] validation 0-auc:0.790371
Will train until validation 0-auc hasn't improved in 5 rounds.
```

```
[1] validation_0-auc:0.811361
[2] validation_0-auc:0.820967
[3] validation 0-auc:0.823629
[4] validation_0-auc:0.823931
[5] validation_0-auc:0.824745
[6] validation 0-auc:0.825439
[7] validation 0-auc:0.82547
[8] validation 0-auc:0.826124
[9] validation 0-auc:0.827535
[10] validation_0-auc:0.829742
[11] validation_0-auc:0.830777
[12] validation 0-auc:0.831048
[13] validation 0-auc:0.830361
[14] validation 0-auc:0.831438
[15] validation_0-auc:0.831822
[16] validation_0-auc:0.832153
[17] validation 0-auc:0.832076
[18] walidation 0-aug.0 832266
```

```
[19] validation_0-auc:0.831917

[20] validation_0-auc:0.83158

[21] validation_0-auc:0.831914

[22] validation_0-auc:0.831441

[23] validation_0-auc:0.831114

Stopping. Best iteration:

[18] validation_0-auc:0.832266
```

In [774]:

```
# CLassification Report
print(classification_report(y_valid_return, y_pred_valid_return))
```

support	f1-score	recall	precision	
311474	1.00	1.00	0.99	0
1952	0.04	0.02	0.36	1
313426	0.99			accuracy
313426	0.52	0.51	0.68	macro avg
313426	0.99	0.99	0.99	weighted avg

In [775]:

```
\label{lem:concurrent} \mbox{[Parallel(n\_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.}
```

```
[Parallel(n jobs=1)]: Done 1 out of 1 | elapsed:
                                                      0.8s remaining:
                                                                        0.0s
[CV] . n_estimators =50, max_depth=8, learning_rate=0.1, total= 0.4s
[CV] n estimators =50, max depth=8, learning rate=0.1 ......
[21:26:35] WARNING: C:/Jenkins/workspace/xgboost-
win64_release_0.90/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] . n_estimators =50, max_depth=8, learning_rate=0.1, total= 0.3s
[CV] n estimators =100, max_depth=12, learning_rate=0.1 .....
[21:26:36] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
req:squarederror.
[CV] n_estimators =100, max_depth=12, learning_rate=0.1, total=
[CV] n_estimators =100, max_depth=12, learning_rate=0.1 .....
[21:26:36] WARNING: C:/Jenkins/workspace/xgboost-
win64_release_0.90/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of
rea: sauarederror.
```

```
[CV] n estimators =100, max depth=12, learning rate=0.1, total= 0.6s
[CV] n estimators =100, max depth=12, learning rate=0.1 .........
[21:26:37] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n estimators =100, max depth=12, learning rate=0.1, total= 0.5s
[CV] n estimators =150, max depth=4, learning rate=0.5 ......
[21:26:37] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n estimators =150, max depth=4, learning rate=0.5, total= 0.2s
[CV] n estimators =150, max depth=4, learning_rate=0.5 ......
[21:26:37] WARNING: C:/Jenkins/workspace/xgboost-
win64_release_0.90/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n estimators =150, max depth=4, learning rate=0.5, total=
[CV] n_estimators =150, max_depth=4, learning_rate=0.5 .....
[21:26:38] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n_estimators =150, max_depth=4, learning_rate=0.5, total= 0.2s
[CV] n estimators =100, max depth=0, learning rate=1 ......
[21:26:38] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] .. n estimators =100, max depth=0, learning rate=1, total= 0.1s
[CV] n estimators =100, max depth=0, learning rate=1 ......
[21:26:38] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] .. n_estimators =100, max_depth=0, learning_rate=1, total= 0.1s
[CV] n estimators =100, max depth=0, learning rate=1 ......
[21:26:38] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] .. n estimators =100, max depth=0, learning rate=1, total= 0.1s
[CV] n_estimators =150, max_depth=9, learning_rate=0.5 ......
[21:26:38] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
req:squarederror.
[CV] n estimators =150, max depth=9, learning rate=0.5, total= 0.4s
[CV] n_estimators =150, max_depth=9, learning_rate=0.5 ......
[21:26:38] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
req:squarederror.
[CV] n estimators =150, max depth=9, learning rate=0.5, total= 0.4s
[CV] n_estimators =150, max_depth=9, learning_rate=0.5 ......
[21:26:39] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
req:squarederror.
[CV] n estimators =150, max depth=9, learning rate=0.5, total= 0.4s
[CV] n estimators =150, max depth=8, learning rate=0.1 ......
[21:26:39] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n estimators =150, max depth=8, learning rate=0.1, total= 0.3s
[CV] n estimators =150, max depth=8, learning rate=0.1 ......
[21:26:40] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n_estimators =150, max_depth=8, learning_rate=0.1, total= 0.4s
[CV] n estimators =150, max depth=8, learning rate=0.1 ......
[21:26:40] WARNING: C:/Jenkins/workspace/xgboost-
\verb|win64_release_0.90/src/objective/regression_obj.cu:152: reg: linear is now deprecated in favor of the control of the contr
reg:squarederror.
[CV] n estimators =150, max depth=8, learning rate=0.1, total= 0.3s
[CV] n estimators =50, max_depth=6, learning_rate=0.01 .....
[21:26:40] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n estimators =50, max depth=6, learning rate=0.01, total=
[CV] n estimators =50, max depth=6, learning rate=0.01 ......
[21:26:41] WARNING: C:/Jenkins/workspace/xgboost-
win64_release_0.90/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n_estimators =50, max_depth=6, learning_rate=0.01, total= 0.3s
[CV] n estimators =50 may denth=6 learning rate=0 01
```

109.090010001101.

```
[CV] II ESCIMATOIS -SU, MAA GEPTH-U, TEATHING TATE-U.UI ..........
[21:26:41] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n_estimators =50, max_depth=6, learning_rate=0.01, total= 0.3s
[CV] n estimators =50, max depth=4, learning rate=0.5 ......
[21:26:41] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
req:squarederror.
[CV] . n estimators =50, max depth=4, learning rate=0.5, total= 0.2s
[CV] n estimators =50, max depth=4, learning rate=0.5 ......
[21:26:41] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
req:squarederror.
[CV] . n estimators =50, max depth=4, learning rate=0.5, total= 0.2s
[CV] n estimators =50, max depth=4, learning rate=0.5 ......
[21:26:41] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] . n estimators =50, max depth=4, learning rate=0.5, total= 0.2s
[CV] n estimators =100, max depth=0, learning rate=0.5 ......
[21:26:42] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n estimators =100, max depth=0, learning rate=0.5, total= 0.1s
[CV] n estimators =100, max depth=0, learning rate=0.5 ......
[21:26:42] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n_estimators =100, max_depth=0, learning_rate=0.5, total=
[CV] n estimators =100, max depth=0, learning rate=0.5 .....
[21:26:42] WARNING: C:/Jenkins/workspace/xgboost-
win64_release_0.90/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n_estimators =100, max_depth=0, learning_rate=0.5, total= 0.1s
[CV] n estimators =150, max depth=2, learning rate=0.01 .........
[21:26:42] WARNING: C:/Jenkins/workspace/xgboost-
win64_release_0.90/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n_estimators =150, max_depth=2, learning_rate=0.01, total= 0.1s
[CV] n estimators =150, max depth=2, learning rate=0.01 .....
[21:26:42] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
req:squarederror.
[CV] n estimators =150, max depth=2, learning rate=0.01, total= 0.1s
[CV] n_estimators =150, max_depth=2, learning_rate=0.01 .....
[21:26:42] WARNING: C:/Jenkins/workspace/xgboost-
win64_release_0.90/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[CV] n estimators =150, max depth=2, learning rate=0.01, total=
[21:26:42] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
reg:squarederror.
[Parallel(n_jobs=1)]: Done 30 out of 30 | elapsed: 8.2s finished
```

Out[775]:

```
RandomizedSearchCV(cv=3, error score='raise-deprecating',
                   estimator=XGBRegressor(base score=0.5, booster='gbtree',
                                           colsample_bylevel=1,
                                           colsample bynode=1,
                                           colsample_bytree=1, gamma=0,
                                           importance_type='gain',
                                           learning rate=0.1, max delta step=0,
                                           max_depth=3, min_child_weight=1,
                                          missing=None, n estimators=100,
                                           n jobs=1, nthread=None,
                                           objective='reg:linear',
                                           random state=0, reg alpha=0,
                                           reg lambda=1, scale pos weight=1,
                                           seed=None, silent=None, subsample=1,
                                           verbosity=1),
                   iid='warn', n_iter=10, n_jobs=None,
                   param distributions={'learning rate': [0.01, 0.1, 0.5, 1],
                                         'max_depth': range(0, 15),
                                         'n estimators ': [50. 100. 1501).
```

```
return train score=False, scoring=None, verbose=2)
In [776]:
xqb best = xqb new.best params
print('Best parameters found by grid search are:', xgb best)
Best parameters found by grid search are: {'n_estimators ': 150, 'max_depth': 2, 'learning_rate':
In [777]:
xqb best = xqb.XGBReqressor(n estimators = 150, max depth = 2, learning rate = 0.01)
xgb best.fit(x train target scaled, y train target)
# Calculating R-square
print("Its R-square of XGboost model is", xqb best.score(x train target scaled, y train target))
# Calculating RMSE for regression
y pred valid target = xgb best.predict(x valid target scaled)
print ("Its RMSE of XGboost model is", np.sqrt (mean squared error (y pred valid target,
y_valid_target)))
[21:27:01] WARNING: C:/Jenkins/workspace/xgboost-
win64 release 0.90/src/objective/regression obj.cu:152: reg:linear is now deprecated in favor of
req:squarederror.
Its R-square of XGboost model is 0.12087742759953268
Its RMSE of XGboost model is 4.134724483858594
In [778]:
y_pred_new = xgb_best.predict(x_test_target_scaled)
In [779]:
y pred new
Out[779]:
array([0.68039453, 0.49469256, 0.38342154, ..., 0.49469256, 0.5691235,
       0.54492813], dtype=float32)
In [780]:
df test1 = pd.read csv(r'C:\Users\ACER\Desktop\UMN\Predictive Analysis\FinalProject\data\test.csv'
,converters={'fullVisitorId': lambda x: str(x)})
In [781]:
#test
data_xgboost_new = {'fullVisitorId': [i for i in df_test1.fullVisitorId], 'PredictedLogRevenue': [j
for j in y pred new]}
submission xgboost new = pd.DataFrame(data xgboost new)
submission_xgboost_new
Out[781]:
              fullVisitorId PredictedLogRevenue
    0 0000018966949534117
                                 0.680395
    1 0000039738481224681
                                 0.494693
    2 0000073585230191399
                                  0.383422
```

3 0000087588448856385

4 0000149787903119437

0.544928

0.494693

.. pre_dispatch='2*n_jobs', random_state=None, refit=True,

```
296525 9999898168621645223 0.407617
296527 999990167740728398 0.494693
296528 9999915620249883537 0.569124
296529 9999947552481876143 0.544928

Z96530 rows × 2 columns

In []:

submission_xgboost_new.to_csv(r'C:\Users\ACER\Desktop\UMN\Predictive Analysis\FinalProject\data\submission_xgboost2.csv', index = False)
```

GA_lightgbm

```
In [1]:
import pandas as pd
# conda install -c conda-forge lightgbm
import lightgbm as lgb
import numpy as np
from sklearn.model_selection import train test split
/anaconda3/lib/python3.7/site-packages/lightgbm/__init__.py:48: UserWarning: Starting from version
2.2.1, the library file in distribution wheels for macOS is built by the Apple Clang (Xcode 8.3.3)
compiler.
This means that in case of installing LightGBM from PyPI via the ``pip install lightgbm`` command,
you don't need to install the gcc compiler anymore.
Instead of that, you need to install the OpenMP library, which is required for running LightGBM on
the system with the Apple Clang compiler.
You can install the OpenMP library by the following command: ``brew install libomp``.
  "You can install the OpenMP library by the following command: ``brew install libomp``.", UserWar
ning)
In [2]:
train = pd.read csv('train final.csv')
test = pd.read csv('test final.csv')
/anaconda3/lib/python3.7/site-packages/IPython/core/interactiveshell.py:3049: DtypeWarning:
Columns (1) have mixed types. Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
In [ ]:
pd.set option('display.max columns', 99)
train.head()
In [3]:
drops = ['isVideoAd mean','Unnamed: 0','isTrueDirect','hits min', 'hits max',
          'hits_median','hits_sd', 'pageviews_min', 'pageviews_max','pageviews_median',
         'pageviews_sd']
train = train.drop(columns = drops)
test = test.drop(columns = drops)
In [4]:
cat = ['channelGrouping','browser','operatingSystem', 'deviceCategory', 'continent',
        'subContinent', 'country', 'region', 'metro', 'city', 'networkDomain', 'source', 'medium']
train[cat] = train[cat].astype('category')
```

```
In [29]:

X_train_all = train.drop(['fullVisitorId','target','ret'], axis = 1)
y_train_all = train['ret']

X_train_ret = train[train['ret'] == 1].drop(['fullVisitorId','target','ret'], axis = 1)
y_train_ret = train[train['ret'] == 1]['target']

X_test = test.drop(['fullVisitorId','target','ret'], axis = 1)

In [30]:

X_train_re, X_test_re, y_train_re, y_test_re = train_test_split(X_train_ret, y_train_ret, test_size)
```

```
=0.33, random_state=42)
X_train_clf, X_test_clf, y_train_clf, y_test_clf = train_test_split(X_train_all, y_train_all, test_size=0.33, random_state=42)
```

Hyperparameters Tuning

|test[cat] = test[cat].astype('category')

```
In [ ]:
```

```
estimator = lgb.LGBMClassifier()

param_grid = {'num_leaves': [40,50,70,90], 'bagging_fraction ' : [0.5,0.7,0.9], 'bagging_freq ': [9
, 10, 11],
    'feature_fraction': [0.4, 0.5, 0.6],
    'learning_rate': [0.001, 0.01, 0.1]
}

lbm_clf = RandomizedSearchCV(estimator, param_distributions = param_grid, cv=5, scoring = 'neg_log_loss')
lbm_clf.fit(X_train_clf, y_train_clf)
print(lbm_clf.best_params_)
```

Train LightGBM Model

```
In [32]:
```

```
dtrain_clf = lgb.Dataset(X_train_clf, label = y_train_clf)
dtest_clf = lgb.Dataset(X_test_clf, label = y_test_clf)
dtrain_re = lgb.Dataset(X_train_re, label = y_train_re)
dtest_re = lgb.Dataset(X_test_re, label = y_test_re)
```

In [33]:

```
#Parameters of "isReturned" classificator
param_lgb2 = {"objective":"binary",
              "num leaves" : 40,
              "learning_rate" : 0.1,
              "bagging_fraction" : 0.5,
              "feature fraction" : 0.4,
              "bagging_frequency" : 11,
              "metric": "binary_logloss"}
#Parameters of "How Much Returned Will Pay" regressor
param_lgb3= {"objective" : "regression",
             "metric" : "rmse",
             "num leaves" : 50,
             "learning_rate" : 0.01,
             "bagging_fraction" : 0.7,
             "feature fraction" : 0.6,
             "bagging frequency" : 9}
```

In [35]:

```
X_train_clf = lgb.Dataset(X_train_all, label = y_train_all)
X_train_re = lgb.Dataset(X_train_re, label = y_train_re)
```

In [37]:

```
pr_lgb_sum = 0
for i in range(10):
    lgb_model1 = lgb.train(param_lgb2, X_train_clf, 65)
    pr_lgb = lgb_model1.predict(X_test)
    lgb_model2 = lgb.train(param_lgb3, X_train_re, 168)
    pr_lgb_ret = lgb_model2.predict(X_test)
    pr_lgb_sum = pr_lgb_sum + pr_lgb * pr_lgb_ret

pr_final2 = (pr_lgb_sum / 10).round(20)
```

In []:

```
df = pd.read_csv('test (1).csv', nrows=1) # Just take the first row to extract the columns' names
col_str_dic = {column:str for column in list(df)}
df = pd.read_csv('test (1).csv', dtype=col_str_dic)

data = {'fullVisitorId': [i for i in df.fullVisitorId], 'PredictedLogRevenue': [j for j in pr_final
2]}
newsub = pd.DataFrame(data)
newsub.to_csv("submission_lgb.csv",index=False)
```

In []:

newsub

Feature importance

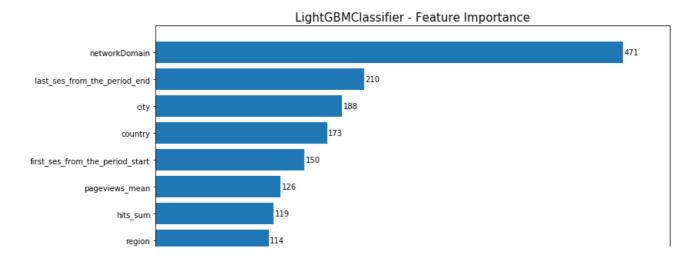
In [39]:

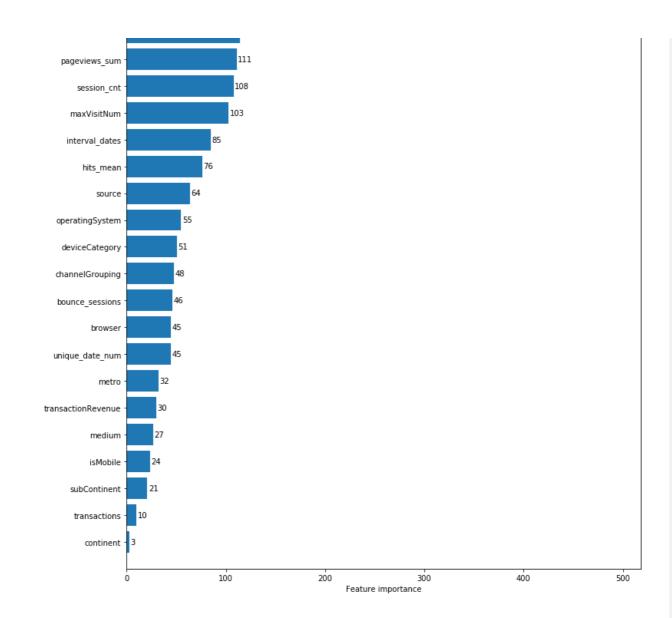
```
import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize=(12,18))
  lgb.plot_importance(lgb_model1, max_num_features=50, height=0.8, ax=ax)
  ax.grid(False)
  plt.title("LightGBMClassifier - Feature Importance", fontsize=15)
  plt.show
```

Out[39]:

<function matplotlib.pyplot.show(*args, **kw)>



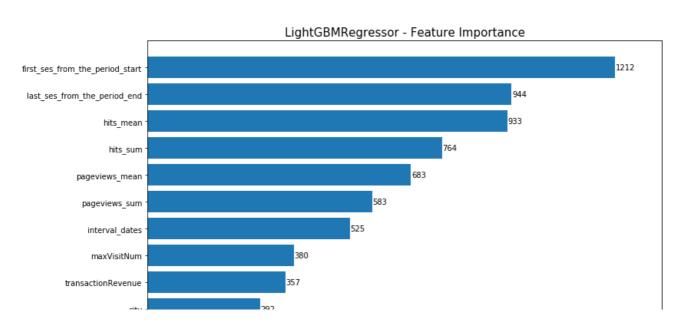


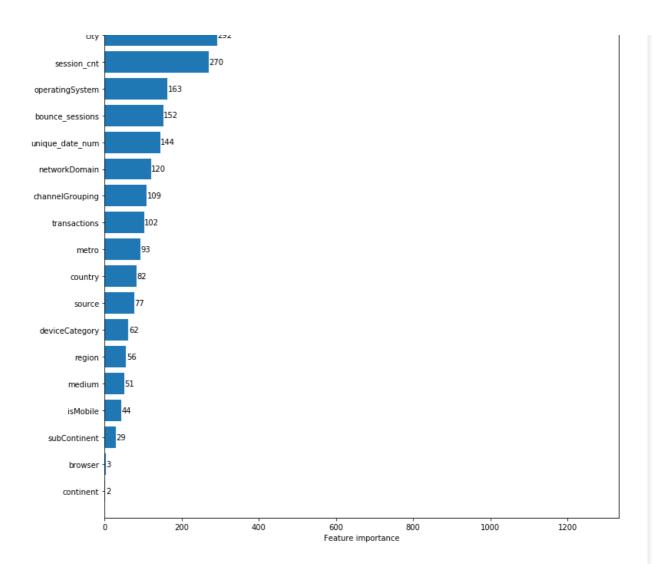
In [40]:

```
fig, ax = plt.subplots(figsize=(12,18))
lgb.plot_importance(lgb_model2, max_num_features=50, height=0.8, ax=ax)
ax.grid(False)
plt.title("LightGBMRegressor - Feature Importance", fontsize=15)
plt.show
```

Out[40]:

<function matplotlib.pyplot.show(*args, **kw)>





Feature Selection

```
In [12]:
```

```
# For CLassification
important_features_for_clf = ['networkDomain',
    'last_ses_from_the_period_end','city','country','first_ses_from_the_period_start',
    'pageviews_mean','hits_sum', 'region','pageviews_sum','session_cnt','maxVisitNum']

X_train_all = X_train_all[important_features_for_clf]

X_test_clf_fs = X_test[important_features_for_clf]
```

In [13]:

In [14]:

```
X_train_re, X_test_re, y_train_re, y_test_re = train_test_split(X_train_ret, y_train_ret, test_size
=0.33, random_state=42)
X_train_clf, X_test_clf, y_train_clf, y_test_clf = train_test_split(X_train_all, y_train_all, test_size=0.33, random_state=42)
```

In [15]:

```
import lightgbm as lgb
from sklearn.metrics import accuracy_score, confusion_matrix,
matthews corrcoef, classification report, roc curve, auc, mean squared error, make scorer, fl score
from math import sqrt
from sklearn.model_selection import cross_val_score, train_test_split, KFold, GridSearchCV,
RandomizedSearchCV
estimator = lgb.LGBMRegressor()
param grid = {'num leaves': [40,50,70,90], 'bagging fraction ': [0.5,0.7,0.9], 'bagging freq ': [9
, 10, 11],
    'feature fraction': [0.4, 0.5, 0.6],
    'learning rate': [0.001, 0.01, 0.1]
lbm re = RandomizedSearchCV(estimator, param distributions = param grid, cv=5, scoring = 'neg mean
squared error')
lbm re.fit(X train re, y train re)
print(lbm re.best params )
{'num_leaves': 40, 'learning_rate': 0.01, 'feature_fraction': 0.6, 'bagging_freq ': 9,
'bagging fraction ': 0.9}
In [16]:
estimator = lgb.LGBMClassifier()
param_grid = {'num_leaves': [40,50,70,90], 'bagging_fraction ' : [0.5,0.7,0.9], 'bagging_freq ': [9
, 10, 11],
    'feature_fraction': [0.4, 0.5, 0.6],
    'learning rate': [0.001, 0.01, 0.1]
lbm clf = RandomizedSearchCV(estimator, param distributions = param grid, cv=5, scoring = 'neg log
lbm clf.fit(X train_clf, y_train_clf)
print(lbm clf.best params )
{'num leaves': 40, 'learning rate': 0.1, 'feature fraction': 0.4, 'bagging freq ': 10,
'bagging fraction ': 0.9}
In [17]:
dtrain_clf = lgb.Dataset(X_train_clf, label = y_train_clf)
dtest_clf = lgb.Dataset(X_test_clf, label = y_test_clf)
dtrain_re = lgb.Dataset(X_train_re, label = y_train_re)
dtest_re = lgb.Dataset(X_test_re, label = y_test_re)
In [18]:
#Parameters of "isReturned" classificator
param lgb2 = {"objective":"binary",
              "num leaves" : 40,
              "learning rate" : 0.01,
              "bagging_fraction" : 0.9,
              "feature fraction" : 0.4,
              "bagging_frequency" : 10,
              "metric": "binary logloss"}
#Parameters of "How Much Returned Will Pay" regressor
param lgb3= {"objective" : "regression",
             "metric" : "rmse",
             "num leaves" : 40,
             "learning rate" : 0.01,
             "bagging fraction" : 0.9,
             "feature fraction" : 0.6,
             "bagging_frequency" : 9}
In [19]:
cat_clf = ['country', 'region', 'city', 'networkDomain']
```

cat re = ['citv']

```
In [20]:
clf model = lgb.train(param lgb2, dtrain clf, 1200, valid sets = [dtest clf],
                       verbose_eval=20, early_stopping_rounds=700, categorical_feature = cat_clf)
/anaconda3/lib/python3.7/site-packages/lightgbm/basic.py:1247: UserWarning: categorical feature in
Dataset is overridden.
New categorical feature is ['city', 'country', 'networkDomain', 'region']
  'New categorical feature is {}'.format(sorted(list(categorical feature))))
Training until validation scores don't improve for 700 rounds
[20] valid 0's binary logloss: 0.0307216
[40] valid 0's binary logloss: 0.0310039
[60] valid_0's binary_logloss: 0.0308969
[80] valid_0's binary_logloss: 0.030863
[100] valid_0's binary_logloss: 0.0308749
[120] valid_0's binary_logloss: 0.0310135
[140] valid_0's binary_logloss: 0.031066
[160] valid_0's binary_logloss: 0.0308067
[180] valid_0's binary_logloss: 0.0308714
[200] valid_0's binary_logloss: 0.0309511
[220] valid_0's binary_logloss: 0.0310635
[240] valid 0's binary_logloss: 0.0311462
[260] valid_0's binary_logloss: 0.031245
[280] valid_0's binary_logloss: 0.031302
[300] valid_0's binary_logloss: 0.0313704
[320] valid_0's binary_logloss: 0.0314337
[340] valid 0's binary logloss: 0.0314795
[360] valid 0's binary logloss: 0.0316051
[380] valid_0's binary_logloss: 0.0316744
[400] valid_0's binary_logloss: 0.0317165
[420] valid_0's binary_logloss: 0.0317842
[440] valid_0's binary_logloss: 0.0318475
[460] valid_0's binary_logloss: 0.0320409
[480] valid_0's binary_logloss: 0.0320953
[500] valid_0's binary_logloss: 0.0321497
[520] valid_0's binary_logloss: 0.0322124 [540] valid_0's binary_logloss: 0.0322738
[560] valid_0's binary_logloss: 0.0323355
[580] valid 0's binary logloss: 0.0324449
[600] valid_0's binary_logloss: 0.0326138
[620] valid_0's binary_logloss: 0.0330917
[640] valid 0's binary logloss: 0.0332603
[660] valid 0's binary logloss: 0.0336325
[680] valid_0's binary_logloss: 0.0336671
[700] valid_0's binary_logloss: 0.0342849
[720] valid_0's binary_logloss: 0.034782
Early stopping, best iteration is:
[31] valid_0's binary_logloss: 0.0303679
In [21]:
re model = lgb.train(param lgb3, dtrain re, 1200, valid sets = [dtest re],
                       verbose_eval=20, early_stopping_rounds=700, categorical_feature = cat re)
/anaconda3/lib/python3.7/site-packages/lightgbm/basic.py:1247: UserWarning: categorical feature in
Dataset is overridden.
New categorical feature is ['city']
  'New categorical feature is {}'.format(sorted(list(categorical feature))))
Training until validation scores don't improve for 700 rounds
[20] valid 0's rmse: 4.04981
[40] valid_0's rmse: 4.00071
[60] valid_0's rmse: 3.96611
[80] valid 0's rmse: 3.94231
[100] valid_0's rmse: 3.93009
[120] valid 0's rmse: 3.92147
[140] valid 0's rmse: 3.91509
[160] valid 0's rmse: 3.91328
[180] valid_0's rmse: 3.91308
```

[200] valid 0's rmse: 3.91404

```
[220] valid 0's rmse: 3.91632
[240] valid 0's rmse: 3.92015
[260] valid 0's rmse: 3.92487
[280] valid 0's rmse: 3.92773
[300] valid_0's rmse: 3.93017
[320] valid 0's rmse: 3.93444
[340] valid 0's rmse: 3.93721
[360] valid 0's rmse: 3.94164
[380] valid 0's rmse: 3.94625
[400] valid_0's rmse: 3.95134
[420] valid_0's rmse: 3.95596
[440] valid 0's rmse: 3.95859
[460] valid_0's rmse: 3.9618
[480] valid 0's rmse: 3.96535
[500] valid 0's rmse: 3.96945
[520] valid_0's rmse: 3.97164
[540] valid 0's rmse: 3.97523
[560] valid 0's rmse: 3.97868
[580] valid 0's rmse: 3.98178
[600] valid 0's rmse: 3.9841
[620] valid 0's rmse: 3.98718
[640] valid_0's rmse: 3.98912
[660] valid_0's rmse: 3.99216
[680] valid_0's rmse: 3.99595
[700] valid 0's rmse: 3.99871
[720] valid_0's rmse: 4.00107
[740] valid_0's rmse: 4.00339
[760] valid 0's rmse: 4.00601
[780] valid 0's rmse: 4.00715
[800] valid 0's rmse: 4.00976
[820] valid 0's rmse: 4.01134
[840] valid_0's rmse: 4.01405
[860] valid_0's rmse: 4.01721
[880] valid 0's rmse: 4.01904
Early stopping, best iteration is:
[186] valid 0's rmse: 3.91213
In [22]:
X train clf = lgb.Dataset(X_train_all, label = y_train_all)
X train re = lgb.Dataset(X train ret, label = y train ret)
In [25]:
pr lgb sum = 0
for i in range(10):
    lgb_model1 = lgb.train(param_lgb2, X_train_clf, 345)
    pr lgb = lgb model1.predict(X test clf fs)
    lgb model2 = lgb.train(param lgb3, X train re,
    pr lgb ret = lgb model2.predict(X test re fs)
    pr_lgb_sum = pr_lgb_sum + pr_lgb * pr_lgb_ret
pr_final2 = pr_lgb_sum / 10
In [26]:
df = pd.read csv('test (1).csv', nrows=1) # Just take the first row to extract the columns' names
col str dic = {column:str for column in list(df)}
df = pd.read csv('test (1).csv', dtype=col str dic)
data = {'fullVisitorId': [i for i in df.fullVisitorId], 'PredictedLogRevenue': [j for j in pr final
21}
newsub = pd.DataFrame(data)
newsub.to csv("submission lgb fs.csv",index=False)
In [ ]:
```