Assignment-Decision-Trees

When the new visitor visits the website, we get the information about source, medium, campaign, deviceCategory, operatingSystem, city, channelGrouping, pageviews, timeOnSite, bounce, etc. Based on these information here build model to predict if the new visitor will transact or not.

Programming langauge : Python
IDE : Jupyter
Dataset link : [https://storage.googleapis.com/sample_user_behavior_data/sample_user_data.csv (https://storage.googleapis.com/sample_user_behavior_data/sample_user_data.csv)](https://storage.googleapis.com/sample_user_behavior_data/sample_user_data.csv)
dataset explanations : [https://www.googlemerchandisestore.com/shop.axd/Home?utm_source=Partners&utm_medium=affiliate&utm_campaign=Data%20Share%20Promo (https://www.googlemerchandisestore.com/shop.axd/Home?utm_source=Partners&utm_medium=affiliate&utm_campaign=Data%20Share%20Promo)](https://www.googlemerchandisestore.com/shop.axd/Home?utm_source=Partners&utm_medium=affiliate&utm_campaign=Data%20Share%20Promo)

In [1]:

```
# importing libraries

import pandas as pd
import numpy as np
from datetime import datetime

from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn import tree
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix
from sklearn.tree import DecisionTreeClassifier, export_graphviz
from sklearn.tree import export_graphviz
from sklearn.externals.six import StringIO

import seaborn as sns
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt

import pydotplus
from IPython.display import Image
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\externals\six.py:31: Fu
tureWarning: The module is deprecated in version 0.21 and will be removed
in version 0.23 since we've dropped support for Python 2.7. Please rely on
the official version of six (https://pypi.org/project/six/).
  "(https://pypi.org/project/six/).", FutureWarning)
```

In [2]:

```
data = pd.read_csv("sample_user_data.csv",low_memory=False)
```

In [3]:

```
data.head(5)
```

Out[3]:

	fullVisitorId	VisitNumber	Date	VisitStartTime	bounces	pageviews	timeOn
0	4948410136152642444	1	20170528	1496033409	NaN	5.0	9
1	2556838449093701419	1	20170528	1495991518	NaN	7.0	12
2	3820120288036087392	1	20170528	1495998052	NaN	21.0	6
3	8405342198290114865	1	20170528	1495963334	NaN	4.0	1
4	8190050108423833846	1	20170528	1496029263	NaN	8.0	2

In [4]:

```
data.describe()
```

Out[4]:

	VisitNumber	Date	VisitStartTime	bounces	pageviews	timeOnSite
count	900544.000000	9.005440e+05	9.005440e+05	449146.0	900443.000000	450276.000000
mean	2.263943	2.016587e+07	1.484955e+09	1.0	3.846293	262.238061
std	9.276698	4.697143e+03	9.127926e+06	0.0	7.018797	484.852324
min	1.000000	2.016080e+07	1.491000e+03	1.0	1.000000	1.000000
25%	1.000000	2.016103e+07	1.477544e+09	1.0	1.000000	32.000000
50%	1.000000	2.017011e+07	1.483868e+09	1.0	1.000000	83.000000
75%	1.000000	2.017042e+07	1.492697e+09	1.0	4.000000	258.000000
max	395.000000	2.017073e+07	1.501571e+09	1.0	469.000000	19017.000000

In [5]:

```
data.describe(include=['O'])
```

Out[5]:

	fullVisitorId	source	medium	campaign	deviceCategory	operatingSystem
count	900544	900543	900543	900543	900543	900543
unique	711874	275	7	8	3	20
top	1957458976293878100	(direct)	(none)	(not set)	desktop	Windows
freq	276	369236	369234	872549	662342	348975

In [6]:

```
data['VisitStartTime'] = pd.to_datetime(data['VisitStartTime'],unit='s')
```

In [7]:

```
data.head()
```

Out[7]:

	fullVisitorId	VisitNumber	Date	VisitStartTime	bounces	pageviews	timeOn
0	4948410136152642444	1	20170528	2017-05-29 04:50:09	NaN	5.0	9
1	2556838449093701419	1	20170528	2017-05-28 17:11:58	NaN	7.0	12
2	3820120288036087392	1	20170528	2017-05-28 19:00:52	NaN	21.0	6
3	8405342198290114865	1	20170528	2017-05-28 09:22:14	NaN	4.0	1
4	8190050108423833846	1	20170528	2017-05-29 03:41:03	NaN	8.0	2

In [8]:

```
# extracting year, month, day, hour, minute from date
data['year'] = data['VisitStartTime'].dt.year
data['month'] = data['VisitStartTime'].dt.month
data['day'] = data['VisitStartTime'].dt.day
data['hour'] = data['VisitStartTime'].dt.hour
data['minute'] = data['VisitStartTime'].dt.minute
```

In [9]:

```
# if transactions = NaN,there will be no transaction; else transaction is made, so we r
eplace NaN with 0
data['transactions'].replace(0, np.nan, inplace=True)
```

In [10]:

```
# if bounces = 1, then no transaction; else a transaction is made, so we replace NaN wi
th 0
data['bounces'].fillna(0, inplace=True)

# if pageviews = NaN, there will be no transaction; else transaction is made, so we rep
lace NaN with 0
data['pageviews'].fillna(0, inplace=True)

# if timeOnSite = NaN,there will be no transaction; else transaction is made, so we rep
lace NaN with 0
data['timeOnSite'].fillna(0, inplace=True)

# if transactions = any value ,there will be transaction; write as 1
data['transactions'] = (data['transactions'].notnull()).astype('int')
```

In [11]:

```
data['transactions'].unique()
```

Out[11]:

```
array([0, 1])
```

In [12]:

```
data.columns
```

Out[12]:

```
Index(['fullVisitorId', 'VisitNumber', 'Date', 'VisitStartTime', 'bounce
s',
       'pageviews', 'timeOnSite', 'totalTransactionRevenue', 'transaction
s',
       'source', 'medium', 'campaign', 'deviceCategory', 'operatingSyste
m',
       'mobileDeviceModel', 'city', 'ChannelGrouping', 'year', 'month', 'd
ay',
       'hour', 'minute'],
      dtype='object')
```

In [13]:

```
# visitorid, date and device model are not required
data = data.drop(['fullVisitorId', 'Date', 'mobileDeviceModel'], axis=1)
```

In [15]:

```
data.shape
```

Out[15]:

```
(900544, 19)
```

In [16]:

```
data['city'].value_counts()
```

Out[16]:

```
not available in demo dataset    506468
Mountain View                     40702
(not set)                         34182
New York                          26245
San Francisco                     20255
                                  ...  
Douglasville                          5
Deep River                            5
Daly City                             4
Bozeman                               3
Boise                                 3
Name: city, Length: 649, dtype: int64
```

In [17]:

```
# replacing "not available in demo dataset" and "(not set)" by "Unavailable"
data['city'].replace('not available in demo dataset', 'Unavailable', inplace=True)
data['city'].replace('(not set)', 'Unavailable', inplace=True)
```

The columns 'totals_totalTransactionRevenue' and 'totals_transactions' are dependent on each other. If 'totals_transactions' is NULL, then 'totals_totalTransactionRevenue' should have NULL as well, and vice-versa

In [18]:

```
%%time

# Transaction_Amt and Transactions_Total
for i in range(0, len(data), 1):
    if (pd.isna(data.iloc[i, 7])) and (pd.notna(data.iloc[i, 8])):
        print('ERROR: totals_totalTransactionRevenue missing when totals_transactions n
ot null at row ', i)

    if (pd.isna(data.iloc[i, 8])) and (pd.notna(data.iloc[i, 7])):
        print('ERROR: totals_transactions missing when totals_totalTransactionRevenue i
s not null at row ', i)
```

```
Wall time: 10.1 s
```

In [19]:

```
# no mismatched rows from the above cell, hence replace NaN with 0
data['totalTransactionRevenue'].fillna(0,inplace=True)
data['transactions'].fillna(0,inplace=True)
```

In [20]:

```
data.head()
```

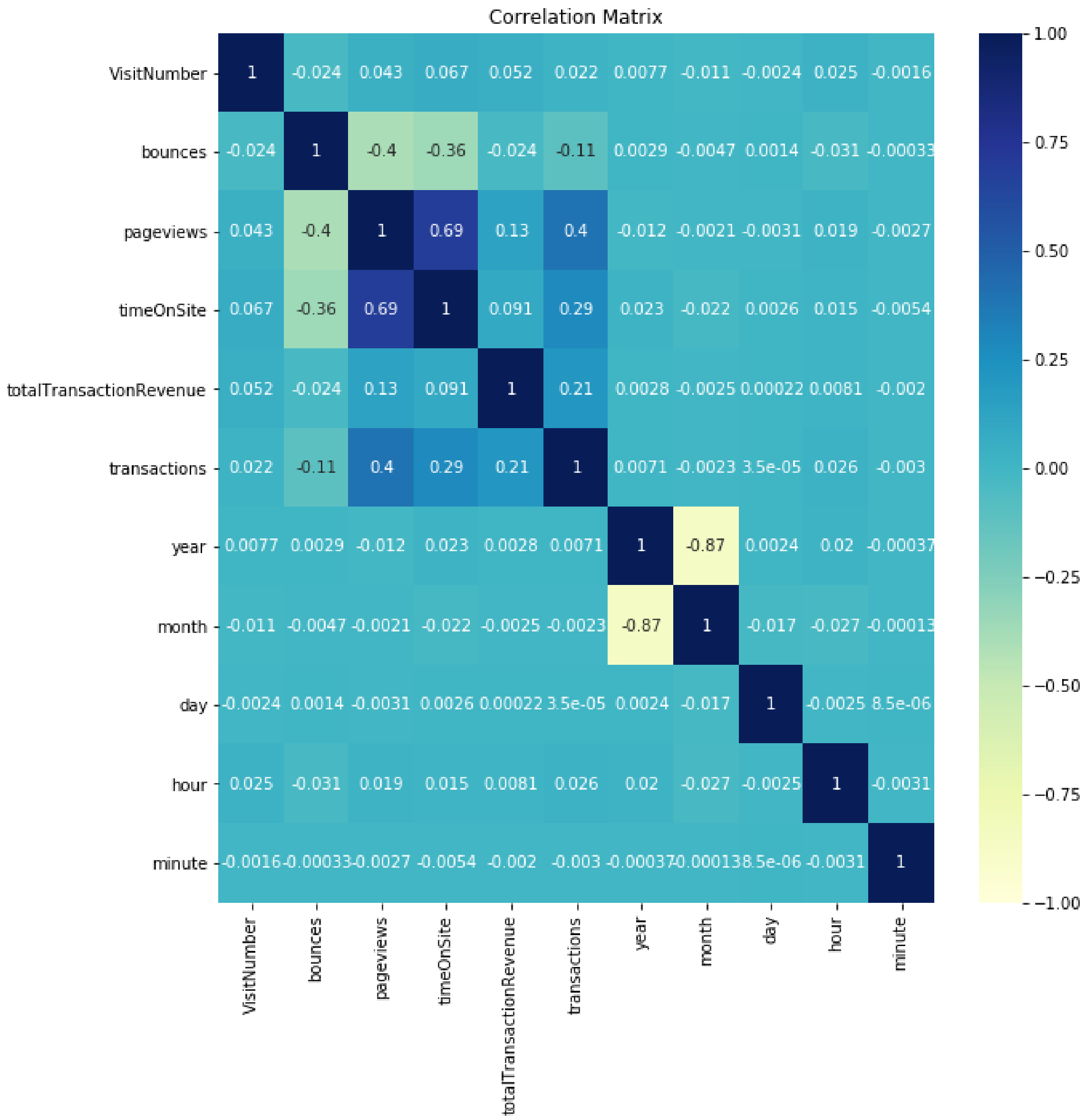
Out[20]:

	VisitNumber	VisitStartTime	bounces	pageviews	timeOnSite	totalTransactionRevenue	tra
0	1	2017-05-29 04:50:09	0.0	5.0	951.0	0.0	
1	1	2017-05-28 17:11:58	0.0	7.0	1214.0	0.0	
2	1	2017-05-28 19:00:52	0.0	21.0	619.0	0.0	
3	1	2017-05-28 09:22:14	0.0	4.0	145.0	0.0	
4	1	2017-05-29 03:41:03	0.0	8.0	267.0	0.0	

HeatMap : find the correlation between each variable and find out the mostaly and related variables.

In [21]:

```
fig1 = plt.figure(figsize = (10,10));
plt.title('Correlation Matrix')
data.corr()
sns.heatmap(data.corr(), vmin = -1, vmax = 1, cmap = 'YlGnBu', annot=True);
```


Correlation Matrix
VisitNumber 1 -0.024 0.043 0.067 0.052 0.022 0.0077 -0.011 -0.0024 0.025 -0.0016
bounces -0.024 1 -0.4 -0.36 -0.024 -0.11 0.0029 -0.0047 0.0014 -0.031 -0.00033
pageviews 0.043 -0.4 1 0.69 0.13 0.4 -0.012 -0.0021 -0.0031 0.019 -0.0027
timeOnSite 0.067 -0.36 0.69 1 0.091 0.29 0.023 -0.022 0.0026 0.015 -0.0054
totalTransactionRevenue 0.052 -0.024 0.13 0.091 1 0.21 0.0028 -0.0025 0.00022 0.0081 -0.002
transactions 0.022 -0.11 0.4 0.29 0.21 1 0.0071 -0.0023 3.5e-05 0.026 -0.003
year 0.0077 0.0029 -0.012 0.023 0.0028 0.0071 1 -0.87 0.0024 0.02 -0.00037
month -0.011 -0.0047 -0.0021 -0.022 -0.0025 -0.0023 -0.87 1 -0.017 -0.027 -0.00013
day -0.0024 0.0014 -0.0031 0.0026 0.00022 3.5e-05 0.0024 -0.017 1 -0.0025 8.5e-06
hour 0.025 -0.031 0.019 0.015 0.0081 0.026 0.02 -0.027 -0.0025 1 -0.0031
minute -0.0016 -0.00033 -0.0027 -0.0054 -0.002 -0.003 -0.00037 -0.00013 8.5e-06 -0.0031 1
VisitNumber bounces pageviews timeOnSite totalTransactionRevenue transactions year month day hour minute
1.00 0.75 0.50 0.25 0.00 −0.25 −0.50 −0.75 −1.00

In [22]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 900544 entries, 0 to 900543
Data columns (total 19 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   VisitNumber            900544 non-null  int64
 1   VisitStartTime         900544 non-null  datetime64[ns]
 2   bounces                900544 non-null  float64
 3   pageviews              900544 non-null  float64
 4   timeOnSite             900544 non-null  float64
 5   totalTransactionRevenue  900544 non-null  float64
 6   transactions           900544 non-null  int32
 7   source                 900543 non-null  object
 8   medium                 900543 non-null  object
 9   campaign               900543 non-null  object
 10  deviceCategory         900543 non-null  object
 11  operatingSystem        900543 non-null  object
 12  city                   900543 non-null  object
 13  ChannelGrouping        900543 non-null  object
 14  year                   900544 non-null  int64
 15  month                  900544 non-null  int64
 16  day                    900544 non-null  int64
 17  hour                   900544 non-null  int64
 18  minute                 900544 non-null  int64
dtypes: datetime64[ns](1), float64(4), int32(1), int64(6), object(7)
memory usage: 127.1+ MB
```

In [24]:

```
#To convert categorical variables to integer using label encoder

labEnc = LabelEncoder()

cols = ["ChannelGrouping", "city", "operatingSystem",
        "campaign", "medium", "source"]

data[cols] = data[cols].astype(str)

col_lessLabels = ["deviceCategory"]

for col in cols:
    data[col] = labEnc.fit_transform(data[col])

data = pd.get_dummies(data, columns = col_lessLabels)
```

In [28]:

```
# Based on the data as we cleaned we split the data into input and output data
# here we want transation output so make these in y varible related variables are in x

features = ['VisitNumber', 'bounces', 'pageviews', 'timeOnSite', 'source',
            'medium', 'campaign', 'operatingSystem', 'city',
            'ChannelGrouping', 'month', 'day', 'hour', 'deviceCategory_desktop', 'devic
eCategory_mobile',
            'deviceCategory_tablet']

# Features
X = data[features]

# Target variable
y = data.transactions
```

In [29]:

```
y.unique()
```

Out[29]:

```
array([0, 1])
```

In [30]:

```
# Split the data into training set and testing set in 80:20 ratio
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
```

In [31]:

```
%%time

# Decision Tree classifer object
Dclf = DecisionTreeClassifier()

# Training Decision Tree Classifer
Dclf = Dclf.fit(X_train,y_train)
```

```
Wall time: 2.15 s
```

In [32]:

```
%%time

#Predict for test dataset
y_pred = Dclf.predict(X_test)
```

```
Wall time: 31.9 ms
```

In [33]:

```
# checking the accuracy of the model

print("Accuracy is:", metrics.accuracy_score(y_test, y_pred))
```

```
Accuracy is: 0.981205825361309
```

Accuracy of the model 0.981205825361309

In [42]:

```
# generating confusion matrix
confusion_matrix(y_test, y_pred)
```

Out[42]:

```
array([[175959,   1828],
       [  1557,    765]], dtype=int64)
```

In [43]:

```
print('Recall = ', (175959 / (175959 + 1828)))
```

```
Recall =  0.9897180333770186
```

Recall of the model 0.9897180333770186

In [56]:

```
print('Precision = ', (175959 / (175959 + 1557)))
```

```
Precision =  0.9912289596430744
```

Precision of the model 0.9912289596430744

CONCLUSION

PREDICTION OF THE MODEL

True Positive = 175959 observations

True Negative = 765 observations

False Positives = 1557 observations

False Negatives = 1828 observations

Recall = HIGH, indicating the classes are correctly identified

Precision = HIGH, indicating the positive class is correctly identified

Now, after training, if we test the model on the test set (which has mostly visitors of the website more than 98 percent chance that that customer will transact),
even if the model predicts that all the 900545 data points have any customer will transact , the accuracy still gets up to a whopping 98%. This can be
misleading especially in a field where the risk of False Negatives should be negligible So we considere the presion and recall value also.

In the model precision higher than recall, higher precision because now the classifier is more confident that the customer has to transact. Lower recall because now that the classifier's threshold is set so high, there will be fewer customer classified as transact.
99 percentage of your results which are relevant,
98.97 percentage of total relevant results correctly classified.

In [ ]:

```

```