AVAZU CTR PROJECT

CTR:In online advertising, click-through rate (CTR) is a very important metric for evaluating ad performance. As a result, click prediction systems are essential and widely used for sponsored search and real-time bidding. Data Rources:[https://www.kaggle.com/c/avazu-ctr-prediction/overview (https://www.kaggle.com/c/avazu-ctr-prediction/overview)](https://www.kaggle.com/c/avazu-ctr-prediction/overview) I randomly choose 20000 units as subset in order to write it as example. The Content for the project.

1. Data Import
2. EDA (Exploratory data analysis)
3. Feature Engineering
4. Model application& Parameter tuning
5. Model Evalutions
6. Next Steps

1. Data import

Evaluation summary Precision: ROI on ad spend through clicks

- low precision means that very little tangible ROI on clicks Recall: targeting on relevant audience
- low recall means missed out opportunties on ROI

In [185]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn. preprocessing import StandardScaler
import sklearn
from sklearn.metrics import confusion_matrix,precision_score,recall_score, roc_c
from sklearn.model_selection import train_test_split
from sklearn. tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import KFold,cross_val_score,GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
```

In [74]:

```
## df=pd.read_csv('train.csv')
```

In [4]:

```
## df_new=df.sample(n=20000)
```

In [75]:

```
df_new=pd.read_csv('df_new.csv')
```

2. EDA

Looked at specific features and variability with CTR dtypes, columns, missing_values, Frequencies,CTR groupby specific features

In [76]:

```
df_new.head()
```

Out[76]:

	Unnamed: 0	id	click	hour	search_engine_type	banner_pos	site_id	site_dc
0	3663003	1.328999e+19	1	14102119	1005	0	1fbe01fe	f38
1	22233842	1.354796e+19	0	14102613	1005	0	89a490f5	ce3
2	24722828	1.367056e+19	0	14102707	1005	0	85f751fd	c4e
3	13789200	1.338143e+19	0	14102404	1005	0	6399eda6	968
4	38864797	1.119810e+18	0	14103014	1005	0	5b08c53b	768

5 rows × 25 columns

In [77]:

```
df_new.dtypes
```

Out[77]:

```
Unnamed: 0              int64
id                    float64
click                   int64
hour                    int64
search_engine_type      int64
banner_pos              int64
site_id                object
site_domain            object
site_category          object
app_id                 object
app_domain             object
app_category           object
device_id              object
device_ip              object
device_model           object
device_type             int64
device_conn_type        int64
C14                     int64
C15                     int64
C16                     int64
C17                     int64
C18                     int64
product_type            int64
C20                     int64
advertiser_type         int64
dtype: object
```

In [78]:

```
1  df_new.columns
```

Out[78]:

```
Index(['Unnamed: 0', 'id', 'click', 'hour', 'search_engine_type', 'ban
ner_pos',
       'site_id', 'site_domain', 'site_category', 'app_id', 'app_domai
n',
       'app_category', 'device_id', 'device_ip', 'device_model', 'devi
ce_type',
       'device_conn_type', 'C14', 'C15', 'C16', 'C17', 'C18', 'product
_type',
       'C20', 'advertiser_type'],
      dtype='object')
```

In [79]:

```
1  np.sum(df_new.isnull())
```

Out[79]:

```
Unnamed: 0            0
id                    0
click                 0
hour                  0
search_engine_type    0
banner_pos            0
site_id               0
site_domain           0
site_category         0
app_id                0
app_domain            0
app_category          0
device_id             0
device_ip             0
device_model          0
device_type           0
device_conn_type      0
C14                   0
C15                   0
C16                   0
C17                   0
C18                   0
product_type          0
C20                   0
advertiser_type       0
dtype: int64
```

In [80]:

```
1  df_new.isnull().sum(axis=1).sum()
```

Out[80]:

```
0
```

In [81]:

```
df_new=df_new.rename(columns={'C1':'search_engine_type','C19':'product_type','C2
```

In [82]:

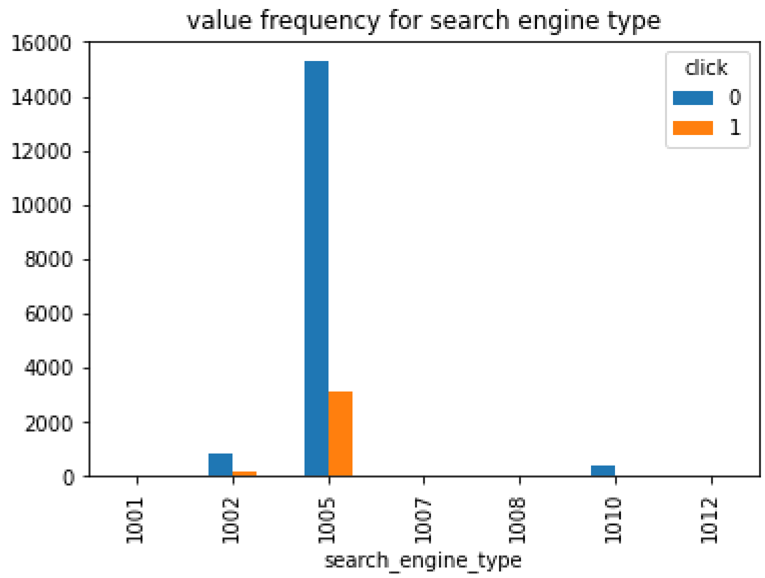
```
se_df=df_new.groupby(['search_engine_type','click']).size().unstack()
```

In [83]:

```
se_df.plot(kind='bar',title='value frequency for search engine type')
```

Out[83]:

```
<AxesSubplot:title={'center':'value frequency for search engine typ
e'}, xlabel='search_engine_type'>
```



In [84]:

```
se_df=se_df.reset_index()
se_df=se_df.rename(columns={0:'non_clicks',1:'clicks'})
```

In [85]:

```
## CTR for different search engine type
se_df['total']=se_df['non_clicks']+se_df['clicks']
se_df['CTR']=se_df['clicks']/se_df['total']
print(se_df.sort_values(by='CTR'))
```

```
click  search_engine_type  non_clicks  clicks    total       CTR
0                    1001         6.0     NaN      NaN       NaN
1                    1002       874.0   208.0   1082.0  0.192237
2                    1005     15268.0  3115.0  18383.0  0.169450
3                    1007        19.0     2.0     21.0  0.095238
4                    1008         6.0     NaN      NaN       NaN
5                    1010       408.0    46.0    454.0  0.101322
6                    1012        39.0     9.0     48.0  0.187500
```

In [196]:

```
## CTR for different product type
se_df=df_new.groupby(['product_type','click']).size().unstack()
se_df=se_df.reset_index()
se_df=se_df.rename(columns={0:'non_clicks',1:'clicks'})
se_df['total']=se_df['non_clicks']+se_df['clicks']
se_df['CTR']=se_df['clicks']/se_df['total']
print(se_df.sort_values(by='CTR'))
```

```
click  product_type  non_clicks  clicks  total       CTR
9               161       738.0    19.0  757.0  0.025099
31              559        24.0     1.0   25.0  0.040000
33              675        44.0     2.0   46.0  0.043478
22              419       164.0     8.0  172.0  0.046512
39              803       210.0    12.0  222.0  0.054054
..              ...         ...     ...    ...       ...
36              683         1.0     NaN    NaN       NaN
46              939         NaN     3.0    NaN       NaN
47              943         5.0     NaN    NaN       NaN
57             1583         3.0     NaN    NaN       NaN
60             1835        11.0     NaN    NaN       NaN

[62 rows x 5 columns]
```

In [198]:

```
## CTR for different advertiser_type
se_df=df_new.groupby(['advertiser_type','click']).size().unstack()
se_df=se_df.reset_index()
se_df=se_df.rename(columns={0:'non_clicks',1:'clicks'})
se_df['total']=se_df['non_clicks']+se_df['clicks']
se_df['CTR']=se_df['clicks']/se_df['total']
print(se_df.sort_values(by='CTR'))
```

```
click  advertiser_type  non_clicks  clicks   total       CTR
50                 204        45.0     1.0    46.0  0.021739
21                  76        72.0     2.0    74.0  0.027027
20                  71       967.0    33.0  1000.0  0.033000
34                 110        73.0     4.0    77.0  0.051948
55                 246       105.0     6.0   111.0  0.054054
54                 229       210.0    12.0   222.0  0.054054
56                 251        17.0     1.0    18.0  0.055556
28                  95       133.0     8.0   141.0  0.056738
40                 156       164.0    10.0   174.0  0.057471
16                  61       966.0    62.0  1028.0  0.060311
30                 101        31.0     2.0    33.0  0.060606
51                 212       307.0    22.0   329.0  0.066869
4                   17        75.0     6.0    81.0  0.074074
47                 182        25.0     2.0    27.0  0.074074
25                  91        56.0     5.0    61.0  0.081967
11                  43       279.0    25.0   304.0  0.082237
44                 171        41.0     4.0    45.0  0.088889
12                  46        85.0     9.0    94.0  0.095745
35                 111        75.0     9.0    84.0  0.107143
27                  94        16.0     2.0    18.0  0.111111
42                 159       119.0    16.0   135.0  0.118519
41                 157       818.0   110.0   928.0  0.118534
13                  48       966.0   130.0  1096.0  0.118613
18                  69        74.0    10.0    84.0  0.119048
36                 112        35.0     5.0    40.0  0.125000
17                  68       130.0    19.0   149.0  0.127517
24                  90        64.0    10.0    74.0  0.135135
10                  42       458.0    73.0   531.0  0.137476
5                   20         6.0     1.0     7.0  0.142857
53                 221      2094.0   402.0  2496.0  0.161058
29                 100        20.0     4.0    24.0  0.166667
33                 108        14.0     3.0    17.0  0.176471
57                 253        35.0     8.0    43.0  0.186047
31                 102         4.0     1.0     5.0  0.200000
22                  79      1739.0   439.0  2178.0  0.201561
14                  51       325.0    83.0   408.0  0.203431
6                   23      3508.0   916.0  4424.0  0.207052
7                   32       726.0   197.0   923.0  0.213434
38                 117       162.0    44.0   206.0  0.213592
1                   13       147.0    41.0   188.0  0.218085
2                   15       284.0    90.0   374.0  0.240642
19                  70        43.0    14.0    57.0  0.245614
3                   16       133.0    47.0   180.0  0.261111
15                  52       427.0   153.0   580.0  0.263793
23                  82        23.0    10.0    33.0  0.303030
49                 195         2.0     1.0     3.0  0.333333
8                   33       460.0   315.0   775.0  0.406452
9                   35        11.0    11.0    22.0  0.500000
58                 255         1.0     2.0     3.0  0.666667
0                    1         1.0     NaN     NaN       NaN
```

26	93	7.0	NaN	NaN	NaN
32	104	3.0	NaN	NaN	NaN
37	116	7.0	NaN	NaN	NaN
39	126	6.0	NaN	NaN	NaN
43	163	1.0	NaN	NaN	NaN
45	177	4.0	NaN	NaN	NaN
46	178	17.0	NaN	NaN	NaN
48	194	2.0	NaN	NaN	NaN
52	219	2.0	NaN	NaN	NaN

3. Feature engineering

(1)Variable processing create hour --- hour of day (2)categorial processing hash(x) (3)features_count (4)Standarization 4.1 Apply log normalization on columns with higher than median variance 4.2 Transform columns using StandardScaler

Variable processing

In [86]:

```
df_new['hour'] = pd.to_datetime(df_new['hour'], format = '%y%m%d%H')
df_new['hour_of_day'] = df_new['hour'].dt.hour
```

In [87]:

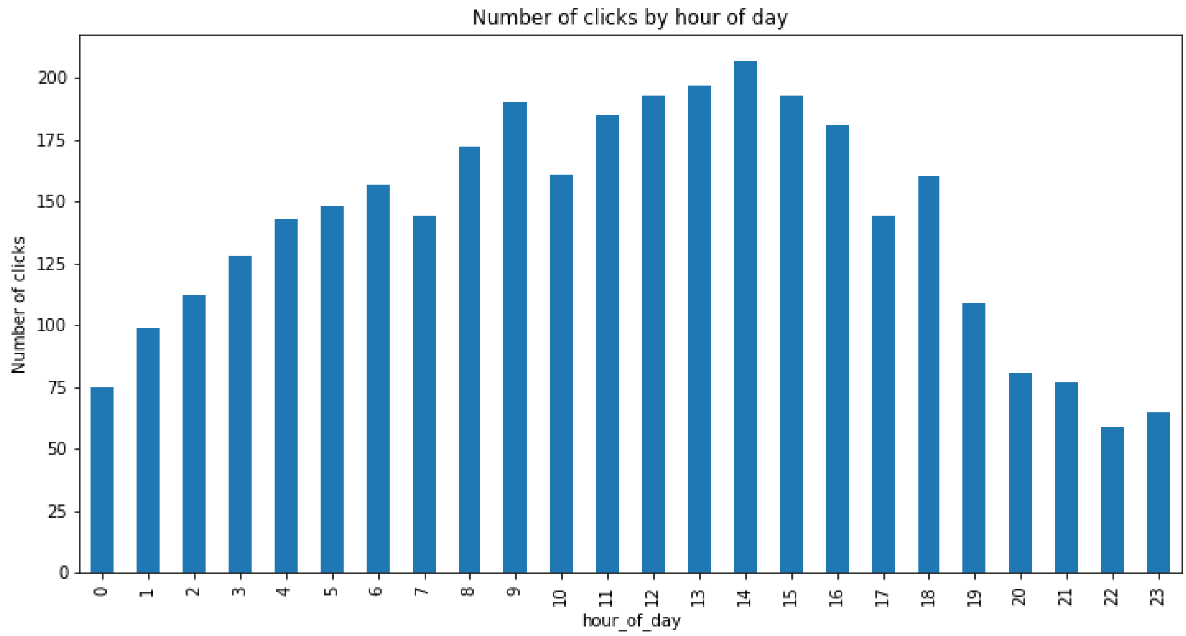
```
print(df_new)
```

```
       Unnamed: 0            id  click                hour  \
0         3663003  1.328999e+19      1 2014-10-21 19:00:00
1        22233842  1.354796e+19      0 2014-10-26 13:00:00
2        24722828  1.367056e+19      0 2014-10-27 07:00:00
3        13789200  1.338143e+19      0 2014-10-24 04:00:00
4        38864797  1.119810e+18      0 2014-10-30 14:00:00
...           ...           ...    ...                 ...
19995    36981302  1.167163e+19      0 2014-10-30 05:00:00
19996    38647342  1.343334e+19      0 2014-10-30 13:00:00
19997    25610131  1.568756e+19      0 2014-10-27 13:00:00
19998    36320507  1.420271e+19      0 2014-10-30 01:00:00
19999    30466462  7.561137e+18      0 2014-10-28 14:00:00

       search_engine_type  banner_pos   site_id site_domain site_categ
ory  \
0                    1005           0  1fbe01fe    f3845767      28905
ebd
1                    1005           0  89a490f5    ce307e01      3e814
130
2                    1005           0  85f751fd    c4e18dd6      50e21
9e0
3                    1005           0  6399eda6    968765cd      f0287
72b
4                    1005           0  5b08c53b    7687a86e      3e814
130
...                   ...         ...       ...         ...
...
19995                1005           1  b7e9786d    b12b9f85      f0287
72b
19996                1005           1  85f751fd    c4e18dd6      50e21
9e0
19997                1005           0  1fbe01fe    f3845767      28905
ebd
19998                1005           0  85f751fd    c4e18dd6      50e21
9e0
19999                1005           1  b7e9786d    b12b9f85      f0287
72b

         app_id  ... device_conn_type    C14  C15  C16   C17  C18  \
0      ecad2386  ...                0  21725  320   50  2502    0
1      ecad2386  ...                0  20009  320   50  2283    0
2      9c13b419  ...                0  18091  320   50  2060    3
3      ecad2386  ...                2  19950  320   50  1800    3
4      ecad2386  ...                0  19016  300  250  2162    2
...         ...  ...              ...    ...  ...  ...   ...  ...
19995  ecad2386  ...                0  19771  320   50  2227    0
19996  cf0327f9  ...                0  23379  300   50  2681    1
19997  ecad2386  ...                0  20108  320   50  2299    2
19998  0acbeaa3  ...                0  22624  320   50  2374    3
19999  ecad2386  ...                0  19772  320   50  2227    0

       product_type     C20  advertiser_type  hour_of_day
0                35  100083              221           19
1               163  100076               95           13
2                39      -1               23            7
3               167  100075               23            4
4                39      -1               33           14
```

```
...            ...     ...         ...         ...
19995          935  100074          48           5
19996          419      -1         212          13
19997         1327      -1          52          13
19998           39      -1          23           1
19999          935  100077          48          14

[20000 rows x 26 columns]
```

In [88]:

```python
# Get and plot total clicks by hour of day
df_new.groupby('hour_of_day')['click'].sum().plot.bar(figsize=(12,6))
plt.ylabel('Number of clicks')
plt.title('Number of clicks by hour of day')
plt.show()
```



In [89]:

```python
##categorial processing
categorial_cols=df_new.select_dtypes(include=['object']).columns.tolist()
for col in categorial_cols:
    df_new[col]= df_new[col].apply(lambda x:hash(x))
```

In [90]:

```
df_new.head()
```

Out[90]:

	Unnamed: 0	id	click	hour	search_engine_type	banner_pos	site
0	3663003	1.328999e+19	1	2014-10-21 19:00:00	1005	0	4434902062798931
1	22233842	1.354796e+19	0	2014-10-26 13:00:00	1005	0	-7509233640368011
2	24722828	1.367056e+19	0	2014-10-27 07:00:00	1005	0	-6648841929243426
3	13789200	1.338143e+19	0	2014-10-24 04:00:00	1005	0	5362171089439795
4	38864797	1.119810e+18	0	2014-10-30 14:00:00	1005	0	469122119204043

5 rows × 26 columns

In [91]:

```
# Get counts of total and unique values for given features
feature_list = ["search_engine_type", "product_type", "advertiser_type"]
for feature in feature_list:
    print(df_new[feature].count())
    print(df_new[feature].nunique())
```

```
20000
7
20000
62
20000
59
```

In [92]:

```
new_feature_list = ['device_id', 'site_id'] + feature_list
for new_feature in new_feature_list:
    df_new[new_feature + '_count'] = df_new.groupby(
    new_feature)['click'].transform("count")
print(df_new.head(5))
```

```
   Unnamed: 0            id  click                hour  search_engine_
type  \
0     3663003  1.328999e+19      1 2014-10-21 19:00:00
1005
1    22233842  1.354796e+19      0 2014-10-26 13:00:00
1005
2    24722828  1.367056e+19      0 2014-10-27 07:00:00
1005
3    13789200  1.338143e+19      0 2014-10-24 04:00:00
1005
4    38864797  1.119810e+18      0 2014-10-30 14:00:00
1005

   banner_pos              site_id          site_domain         site_ca
tegory  \
0           0  4434902062798931880 -7949737045604288452 -2522620493032
896879
1           0 -7509233640368011396  4108338812881778546  3107277090511
135029
2           0 -6648841929243426612  -540229382530709525 -6502660151715
606893
3           0  5362171089439795233  8071600283347957249 -4782788504019
978487
4           0   469122119204043543  7863201858812251847  3107277090511
135029

                app_id  ...  C18  product_type     C20  advertiser_typ
e  \
0 -6372487308215151456  ...    0            35  100083              22
1
1 -6372487308215151456  ...    0           163  100076               9
5
2  8970105218406350399  ...    3            39      -1               2
3
3 -6372487308215151456  ...    3           167  100075               2
3
4 -6372487308215151456  ...    2            39      -1               3
3

   hour_of_day  device_id_count  site_id_count  search_engine_type_cou
nt  \
0           19            16491           3117                     183
83
1           13            16491             42                     183
83
2            7            16491           7242                     183
83
3            4            16491            188                     183
83
4           14            16491            477                     183
83

   product_type_count  advertiser_type_count
```

```
0              5994              2496
1               435               141
2              4433              4424
3              1577              4424
4              4433               775

[5 rows x 31 columns]
```

Standarization

In [93]:

```
num_df = df_new.select_dtypes(include=['int', 'float'])
print(num_df.columns)
```

```
Index(['Unnamed: 0', 'id', 'click', 'search_engine_type', 'banner_po
s',
       'site_id', 'site_domain', 'site_category', 'app_id', 'app_domai
n',
       'app_category', 'device_id', 'device_ip', 'device_model', 'devi
ce_type',
       'device_conn_type', 'C14', 'C15', 'C16', 'C17', 'C18', 'product
_type',
       'C20', 'advertiser_type', 'hour_of_day', 'device_id_count',
       'site_id_count', 'search_engine_type_count', 'product_type_coun
t',
       'advertiser_type_count'],
      dtype='object')
```

In [94]:

```
filter_cols = ['click', 'banner_pos', 'device_type',
               'search_engine_type', 'product_type', 'advertiser_type']
new_df = num_df[num_df.columns[~num_df.columns.isin(filter_cols)]]
print(new_df.columns)
median = new_df.var().median()
print(median)
```

```
Index(['Unnamed: 0', 'id', 'site_id', 'site_domain', 'site_category',
'app_id',
       'app_domain', 'app_category', 'device_id', 'device_ip', 'device
_model',
       'device_conn_type', 'C14', 'C15', 'C16', 'C17', 'C18', 'C20',
       'hour_of_day', 'device_id_count', 'site_id_count',
       'search_engine_type_count', 'product_type_count',
       'advertiser_type_count'],
      dtype='object')
1268691659.4780107
```

In [95]:

```
# Apply log normalization on columns with higher than median variance
change_cols = new_df.columns[new_df.var() > median].tolist()
new_df[change_cols] = new_df[change_cols].apply(
  lambda x: np.log(x))
print(new_df.var().median())
```

```
1.6925290263834554

/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/pandas/cor
e/arraylike.py:358: RuntimeWarning: invalid value encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/pandas/cor
e/frame.py:3191: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
 (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  self[k1] = value[k2]
```

In [96]:

```
# Transform columns using StandardScaler
scaler =StandardScaler()
df_new[num_cols] = scaler.fit_transform(df_new[num_cols])
# Print mean and variance of transformed columns
print(df_new[num_cols].mean())
print(df_new[num_cols].var())
```

```
id                          -4.959921e-18
site_id                     -1.639466e-16
device_conn_type            -2.990663e-16
device_id_count             -2.609302e-16
site_id_count                2.062905e-16
search_engine_type_count     8.708423e-16
product_type_count           3.049894e-16
advertiser_type_count        9.018897e-17
dtype: float64
id                           1.00005
site_id                      1.00005
device_conn_type             1.00005
device_id_count              1.00005
site_id_count                1.00005
search_engine_type_count     1.00005
product_type_count           1.00005
advertiser_type_count        1.00005
dtype: float64
```

In [97]:

```
df_new.columns
```

Out[97]:

```
Index(['Unnamed: 0', 'id', 'click', 'hour', 'search_engine_type', 'ban
ner_pos',
       'site_id', 'site_domain', 'site_category', 'app_id', 'app_domai
n',
       'app_category', 'device_id', 'device_ip', 'device_model', 'devi
ce_type',
       'device_conn_type', 'C14', 'C15', 'C16', 'C17', 'C18', 'product
_type',
       'C20', 'advertiser_type', 'hour_of_day', 'device_id_count',
       'site_id_count', 'search_engine_type_count', 'product_type_coun
t',
       'advertiser_type_count'],
      dtype='object')
```

4. Model Application & Parameters tuning

(1) Logitic Regression (2) Decision Tree (3) Random Forest (4) MLPClassifier Create list of hyperparameters Use Grid search CV to find best parameters

In [99]:

```
# Set up classifier using training data to predict test data
x=df_new.loc[:,~df_new.columns.isin(['click'])]
```

In [107]:

```
df_new.columns
```

Out[107]:

```
Index(['Unnamed: 0', 'id', 'click', 'hour', 'search_engine_type', 'ban
ner_pos',
       'site_id', 'site_domain', 'site_category', 'app_id', 'app_domai
n',
       'app_category', 'device_id', 'device_ip', 'device_model', 'devi
ce_type',
       'device_conn_type', 'C14', 'C15', 'C16', 'C17', 'C18', 'product
_type',
       'C20', 'advertiser_type', 'hour_of_day', 'device_id_count',
       'site_id_count', 'search_engine_type_count', 'product_type_coun
t',
       'advertiser_type_count'],
      dtype='object')
```

In [111]:

```
filter_cols = ['hour', 'search_engine_type', 'banner_pos',
       'site_id', 'site_domain', 'site_category', 'app_id', 'app_domain',
       'app_category', 'device_id', 'device_ip', 'device_model', 'device_type',
       'device_conn_type','product_type',
       'C20', 'advertiser_type', 'hour_of_day', 'device_id_count',
       'site_id_count', 'search_engine_type_count', 'product_type_count',
       'advertiser_type_count']
new_df2 = df_new.loc[:,df_new.columns.isin(filter_cols)]
print(new_df2.columns)
```

```
Index(['hour', 'search_engine_type', 'banner_pos', 'site_id', 'site_do
main',
       'site_category', 'app_id', 'app_domain', 'app_category', 'devic
e_id',
       'device_ip', 'device_model', 'device_type', 'device_conn_type',
       'product_type', 'C20', 'advertiser_type', 'hour_of_day',
       'device_id_count', 'site_id_count', 'search_engine_type_count',
       'product_type_count', 'advertiser_type_count'],
      dtype='object')
```

In [129]:

```
new_df2['hour']=pd.to_numeric(new_df2['hour'])
```

```
<ipython-input-129-da1a88d46981>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
 (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  new_df2['hour']=pd.to_numeric(new_df2['hour'])
```

In [112]:

```
y=df_new.click
```

In [106]:

```
#CTR
print("sample CTR :\n",y.sum()/len(y))
```

```
sample CTR :
 0.169
```

In [ ]:

```
x_train, x_test, y_train, y_test = train_test_split(
  new_df2, y, test_size = .2, random_state = 0)
```

DecisionTree

In [130]:

```
clf = DecisionTreeClassifier()
```

In [131]:

```
y_pred = clf.fit(x_train, y_train).predict(x_test)
```

In [134]:

```
# Define confusion matrix and four categories
conf_matrix = confusion_matrix(y_test, y_pred)
tn = conf_matrix[0][0]
fp = conf_matrix[0][1]
fn = conf_matrix[1][0]
tp = conf_matrix[1][1]

print("TN: %s, FP: %s, FN: %s, TP: %s" %(tn, fp, fn, tp))
```

```
TN: 2785, FP: 589, FN: 459, TP: 167
```

In [135]:

```
## ROI
# Calculate total return, total spent, and ROI
r = 0.2
cost = 0.05
total_return = tp * r
total_cost = (tp + fp) * cost
roi = total_return / total_cost
print("Total return: %s, Total cost: %s, ROI: %s" %(
  total_return, total_cost, roi))
```

```
Total return: 33.4, Total cost: 37.800000000000004, ROI: 0.88359788359
78835
```

In [138]:

```
### Evaluate precision and recall
prec = precision_score(y_test, y_pred, average = 'weighted')
recall = recall_score(y_test, y_pred, average = 'weighted')
print("Precision: %s, Recall: %s" %(prec, recall))
```

```
Precision: 0.758722277676655, Recall: 0.738
```

Logistic regression

In [187]:

```
# Create and fit classifier
clf = LogisticRegression()
y_pred = clf.fit(x_train, y_train).predict(x_test)
y_score = clf.fit(x_train, y_train).predict_proba(x_test)
# Calculate total return, total spent, and ROI
r, cost = 0.2, 0.05
tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
total_return = tp * r
total_spent = (tp + fp) * cost
roi = total_return / total_spent
prec = precision_score(y_test, y_pred, average = 'weighted')
roc_auc = roc_auc_score(y_test, y_score[:, 1])
print("ROI: %s, Precision: %s,AUC of ROC curve:%s" %( roi, prec, roc_auc))
```

```
ROI: nan, Precision: 0.697225,AUC of ROC curve:0.6225880058065687

<ipython-input-187-6611609ed55c>:10: RuntimeWarning: invalid value enc
ountered in double_scalars
  roi = total_return / total_spent
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/me
trics/_classification.py:1248: UndefinedMetricWarning: Precision is il
l-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Not works..Choose Decision Tree model

Optimization

Decision Tree

In [165]:

```
for max_depth_val in [2, 3, 5, 10, 15, 20]:
    k_fold = KFold(n_splits= 4)
    clf = DecisionTreeClassifier(max_depth = max_depth_val)
    print("Evaluating Decision Tree for max_depth = %s" %(max_depth_val))
    y_pred = clf.fit(x_train, y_train).predict(x_test)

  # Calculate precision for cross validation and test
    cv_precision = cross_val_score(
    clf, x_train, y_train, cv = k_fold, scoring = 'precision_weighted')
    precision = precision_score(y_test, y_pred, average = 'weighted')
    print("Cross validation Precision: %s" %(cv_precision))
    print("Test Precision: %s" %(precision))
```

```
Evaluating Decision Tree for max_depth = 2
Cross validation Precision: [0.68434256 0.68517006 0.674041   0.698060
25]
Test Precision: 0.71149225
Evaluating Decision Tree for max_depth = 3

/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/me
trics/_classification.py:1248: UndefinedMetricWarning: Precision is il
l-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/me
trics/_classification.py:1248: UndefinedMetricWarning: Precision is il
l-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/me
trics/_classification.py:1248: UndefinedMetricWarning: Precision is il
l-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/me
trics/_classification.py:1248: UndefinedMetricWarning: Precision is il
l-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/me
trics/_classification.py:1248: UndefinedMetricWarning: Precision is il
l-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/me
trics/_classification.py:1248: UndefinedMetricWarning: Precision is il
l-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/me
trics/_classification.py:1248: UndefinedMetricWarning: Precision is il
l-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/me
trics/_classification.py:1248: UndefinedMetricWarning: Precision is il
l-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/me
trics/_classification.py:1248: UndefinedMetricWarning: Precision is il
l-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

Cross validation Precision: [0.68434256 0.68517006 0.674041   0.753318
04]
Test Precision: 0.71149225
Evaluating Decision Tree for max_depth = 5
Cross validation Precision: [0.76391849 0.77079215 0.75557574 0.745415
96]
Test Precision: 0.7702151973131822
Evaluating Decision Tree for max_depth = 10
Cross validation Precision: [0.74834542 0.74687128 0.74211881 0.750794
2 ]
Test Precision: 0.7610478957019544
Evaluating Decision Tree for max_depth = 15
Cross validation Precision: [0.74271706 0.73899492 0.74423279 0.747961
35]
Test Precision: 0.7603252855120273
Evaluating Decision Tree for max_depth = 20
Cross validation Precision: [0.74425977 0.74457349 0.73348737 0.745763
53]
Test Precision: 0.7648198952784833
```

In [183]:

```
# Create model
clf = DecisionTreeClassifier(max_depth=5)

# Set up k-fold
k_fold = KFold()

# Evaluate precision and recall for each fold
precision = cross_val_score(clf, x_train, y_train, cv = k_fold, scoring = 'preci
recall = cross_val_score(clf, x_train, y_train, cv =k_fold, scoring = 'recall_we
fbeta = fbeta_score(y_test, y_pred, beta  = 0.5, average = 'weighted')
print("Precision: %s, Recall: %s, F-Beta : %s" %(precision, recall,fbeta))
```

```
Precision: [0.75606824 0.75714503 0.77294062 0.76431025 0.77851485], R
ecall: [0.8275    0.829375  0.8290625 0.8215625 0.828125 ], F-Beta :
0.7402041684020548
```

Randomforest

In [163]:

```
# Create list of hyperparameters
n_estimators = [10, 20,50,80,100]
max_depth = [3, 5,10,20]
param_grid = {'n_estimators': n_estimators, 'max_depth': max_depth}

# Use Grid search CV to find best parameters
print("starting RF grid search.. ")
rf = RandomForestClassifier()
clf = GridSearchCV(estimator = rf, param_grid = param_grid, scoring = 'roc_auc')
clf.fit(x_train, y_train)
print("Best Score: ")
print(clf.best_score_)
print("Best Estimator: ")
print(clf.best_estimator_)
```

```
starting RF grid search..
Best Score:
0.7037666697116769
Best Estimator:
RandomForestClassifier(max_depth=10, n_estimators=80)
```

In [181]:

```
# Create random forest classifier with specified params
clf = RandomForestClassifier(n_estimators = 80, max_depth = 10)

# Train classifier - predict probability score and label
y_score = clf.fit(x_train, y_train).predict_proba(x_test)
y_pred = clf.fit(x_train, y_train).predict(x_test)

# Get ROC curve metrics
fpr, tpr, thresholds = roc_curve(y_test, y_score[:, 1])
print("ROC of AUC: %s"%(auc(fpr, tpr)))

# Get precision and recall
precision = precision_score(y_test, y_pred, average = 'weighted')
recall = recall_score(y_test, y_pred, average = 'weighted')
fbeta = fbeta_score(y_test, y_pred, beta  = 0.5, average = 'weighted')
print("Precision: %s, Recall: %s, F-Beta : %s" %(precision, recall,fbeta))
```

```
ROC of AUC: 0.6979441117764471
Precision: 0.7846571716662465, Recall: 0.83525, F-Beta : 0.74020416840
20548
```

Deep Learning

In [177]:

```
# Create list of hyperparameters
max_iter = [10, 20,50,100]
hidden_layer_sizes = [(4,),(8,), (16,), (20,)]
param_grid = {'max_iter': max_iter, 'hidden_layer_sizes': hidden_layer_sizes}

# Use Grid search CV to find best parameters using 4 jobs
mlp = MLPClassifier()
clf = GridSearchCV(estimator = mlp, param_grid =param_grid,
            scoring = 'roc_auc', n_jobs = 4)
clf.fit(x_train, y_train)
print("Best Score: ")
print(clf.best_score_)
print("Best Estimator: ")
print(clf.best_estimator_)
```

```
Best Score:
0.6710547262515745
Best Estimator:
MLPClassifier(hidden_layer_sizes=(20,), max_iter=100)

/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/ne
ural_network/_multilayer_perceptron.py:614: ConvergenceWarning: Stocha
stic Optimizer: Maximum iterations (100) reached and the optimization
hasn't converged yet.
  warnings.warn(
```

In [178]:

```
# Scale features and split into training and testing
x = StandardScaler().fit_transform(new_df2)
x_train, x_test, y_train, y_test = train_test_split(
  x, y, test_size = .2)

# Create classifier and produce predictions
clf = MLPClassifier(hidden_layer_sizes = (20, ), max_iter = 100)
y_score = clf.fit(x_train, y_train).predict_proba(x_test)
y_pred = clf.fit(x_train, y_train).predict(x_test)

# Get accuracy and AUC of ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_score[:, 1])
roc_auc = auc(fpr, tpr)
print("Accuracy: %s" %(accuracy_score(y_test, y_pred)))
print("ROC of AUC curve: %s" %(roc_auc))
```

```
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/ne
ural_network/_multilayer_perceptron.py:614: ConvergenceWarning: Stocha
stic Optimizer: Maximum iterations (100) reached and the optimization
hasn't converged yet.
  warnings.warn(

Accuracy: 0.83275
ROC of AUC curve: 0.6635515332970423

/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/ne
ural_network/_multilayer_perceptron.py:614: ConvergenceWarning: Stocha
stic Optimizer: Maximum iterations (100) reached and the optimization
hasn't converged yet.
  warnings.warn(
```

In [180]:

```
# Evaluate precision and recall
prec = precision_score(y_test, y_pred, average = 'weighted')
recall = recall_score(y_test, y_pred, average = 'weighted')
fbeta = fbeta_score(y_test, y_pred, beta  = 0.5, average = 'weighted')
print("Precision: %s, Recall: %s, F-beta score: %s" %(prec, recall, fbeta))
```

```
Precision: 0.7678272235711199, Recall: 0.83275, F-beta score: 0.742211
886845039
```

In [186]:

```
# Evaluate the ROI
prec = precision_score(y_test, y_pred, average = 'weighted')
r = 0.2
cost = 0.05
roi = prec * r / cost
# Get AUC
roc_auc = roc_auc_score(y_test, y_score[:, 1])
print("Total ROI: %s, Precision: %s, AUC of ROC curve: %s" %(
  roi, prec, roc_auc))
```

```
Total ROI: 3.138628686664986, Precision: 0.7846571716662465, AUC of RO
C curve: 0.6979441117764471
```

5. Evaluation

Create list of classifiers Produce a classification report for all classifiers ** ROI(precision_score) *r /cost* * Recall-sensitivity = TP / (TP + FN) ** precision - positive predictive value = TP / (TP + FP) ** F-beta: F-Measure = (2 * Precision * Recall) / (Precision + Recall) ** AUC-ROC score. It tells how much the model is capable of distinguishing between classes.

In [191]:

```
## Model comparsion
# Create list of classifiers
names = ['Logistic Regression',  'Decision Tree',
         'Random Forest', 'Multi-Layer Perceptron']
clfs = [LogisticRegression(),
        DecisionTreeClassifier(max_depth=5),
        RandomForestClassifier(n_estimators = 80, max_depth = 10),
        MLPClassifier(hidden_layer_sizes = (20,), max_iter = 100)]

# Produce a classification report for all classifiers
for name, classifier in zip(names, clfs):
    classifier.fit(x_train, y_train)
    y_score = clf.fit(x_train, y_train).predict_proba(x_test)
    y_pred = classifier.predict(x_test)
    prec = precision_score(y_test, y_pred, average = 'weighted')
    r, cost = 0.2, 0.05
    roi = prec * r / cost
    print("ROI for %s: %s " %(name, roi))
    recall = recall_score(y_test, y_pred, average = 'weighted')
    fbeta = fbeta_score(y_test, y_pred, beta = 0.5, average = 'weighted')
    roc_auc = roc_auc_score(y_test, y_score[:, 1])
    print("Precision: %s: Recall: %s, F-beta score: %s, AUC of ROC curve: %s"
        %(prec, recall, fbeta, roc_auc))
```

```
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/me
trics/_classification.py:1248: UndefinedMetricWarning: Precision is il
l-defined and being set to 0.0 in labels with no predicted samples. Us
e `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

ROI for Logistic Regression: 2.7889
Precision: 0.697225: Recall: 0.835, F-beta score: 0.721018614270941, A
UC of ROC curve: 0.6225880058065687
ROI for Decision Tree: 3.09244918699187
Precision: 0.7731122967479676: Recall: 0.833, F-beta score: 0.74803326
41074762, AUC of ROC curve: 0.6225880058065687
ROI for Random Forest: 3.127923387096774
Precision: 0.7819808467741935: Recall: 0.835, F-beta score: 0.73909667
81548334, AUC of ROC curve: 0.6225880058065687
ROI for Multi-Layer Perceptron: 3.088576222837487
Precision: 0.7721440557093716: Recall: 0.83425, F-beta score: 0.734701
9290765391, AUC of ROC curve: 0.6225880058065687

/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/ne
ural_network/_multilayer_perceptron.py:614: ConvergenceWarning: Stocha
stic Optimizer: Maximum iterations (100) reached and the optimization
hasn't converged yet.
  warnings.warn(
```

6. Next Steps

The evaluation showed that Random's forest's ROI is highest, Decision Tree's F-beta score is highest. Next steps: Use Ensemble modeling to improve the accuracy. Ensemble modeling is a process where multiple diverse models are created to predict an outcome, either by using many different modeling algorithms or using different training data sets.