AppOnBoard Data Modeling Technical Assignment

In [ ]:

```
'''
######## AppOnBoard Data Modeling Technical Assignment ######
 `##### Made by : Rachit Mishra #####
##### AVAZU  -- Click Through rate Prediction #####
   ###### Predict whether an ad will be clicked or not #######
'''
```

Specifying neccessary imports

In [8]:

```
'''Specifying the necessary imports'''
import pandas as pd
import numpy as np
import dask.dataframe as dask_data
#Dask data frames used to help in in-memory large computing on a single machine

#visualization specific imports
import matplotlib
import matplotlib.pyplot as plt
import seaborn
import plotly.graph_objs as go
from plotly.offline import init_notebook_mode, iplot, plot, download_plotlyjs

import sklearn
import matplotlib.dates as mdates
```

In [10]:

```
matplotlib.style.use('ggplot')

#A parse date variable to pass in the read_csv function later to take into account the date format
parse_date = lambda val : pd.datetime.strptime(val, '%y%m%d%H')
```

Sampling the training data

In [11]:

```
''' Specifying a sample of the original training data
    Training data size == 5.87 gigabytes
    Number of records === 40428966 (excess of 40 million records)

    Using random sampling to select a sample of 1 million records
'''

import random
n = 40428966  #total number of records in the clickstream data
sample_size = 1000000
skip_values = sorted(random.sample(range(1,n), n-sample_size))

#Tracking the indices of rows to be skipped at random in the next stage i.e the LOADING stage
```

Data Loading stage

In [13]:

```
''' LOADING stage
    Reading the sampled train data
    Size : 1 million records
'''
```

```
train_data = pd.read_csv('./all/train/train.csv', parse_dates = ['hour'], date_parser = parse_date,
                        skiprows = skip_values )
```

In [14]:

```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000001 entries, 0 to 1000000
Data columns (total 24 columns):
id                  1000001 non-null uint64
click               1000001 non-null int64
hour                1000001 non-null datetime64[ns]
C1                  1000001 non-null int64
banner_pos          1000001 non-null int64
site_id             1000001 non-null object
site_domain         1000001 non-null object
site_category       1000001 non-null object
app_id              1000001 non-null object
app_domain          1000001 non-null object
app_category        1000001 non-null object
device_id           1000001 non-null object
device_ip           1000001 non-null object
device_model        1000001 non-null object
device_type         1000001 non-null int64
device_conn_type    1000001 non-null int64
C14                 1000001 non-null int64
C15                 1000001 non-null int64
C16                 1000001 non-null int64
C17                 1000001 non-null int64
C18                 1000001 non-null int64
C19                 1000001 non-null int64
C20                 1000001 non-null int64
C21                 1000001 non-null int64
dtypes: datetime64[ns](1), int64(13), object(9), uint64(1)
memory usage: 183.1+ MB
```

Memory Optimization

In [307]:

```
'''
Memory optimization at this point ~~ 183 megabytes

Optimization technique ::: Alter data types from int64 to int32 to reduce block memory usage

Then RELOADING the data
'''
data_types = {
    'id': np.str,
    'click': np.bool_,
    'hour': np.str,
    'C1': np.uint16,
    'banner_pos': np.uint16,
    'site_id': np.object,
    'site_domain': np.object,
    'site_category': np.object,
    'app_id': np.object,
    'app_domain': np.object,
    'app_category': np.object,
    'device_id': np.object,
    'device_ip': np.object,
    'device_model': np.object,
    'device_type': np.uint16,
    'device_conn_type': np.uint16,
    'C14': np.uint16,
    'C15': np.uint16,
    'C16': np.uint16,
    'C17': np.uint16,
    'C18': np.uint16,
    'C19': np.uint16,
```

```
    'C20': np.uint16,
    'C21': np.uint16
}

train_data = pd.read_csv('./all/train/train.csv', parse_dates = ['hour'],
                        date_parser = parse_date, skiprows = skip_values ,
                        dtype = data_types )
```

A separate data frame where clicks = 1

In [78]:

```
train_data_clicks = train_data[train_data['click']==1]
```

In [17]:

```
train_data.info()


## Memory consumption reduced to 107.8 + MB

'''
% reduction in memory usage = 40%
'''
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000001 entries, 0 to 1000000
Data columns (total 24 columns):
id                  1000001 non-null object
click               1000001 non-null bool
hour                1000001 non-null datetime64[ns]
C1                  1000001 non-null uint16
banner_pos          1000001 non-null uint16
site_id             1000001 non-null object
site_domain         1000001 non-null object
site_category       1000001 non-null object
app_id              1000001 non-null object
app_domain          1000001 non-null object
app_category        1000001 non-null object
device_id           1000001 non-null object
device_ip           1000001 non-null object
device_model        1000001 non-null object
device_type         1000001 non-null uint16
device_conn_type    1000001 non-null uint16
C14                 1000001 non-null uint16
C15                 1000001 non-null uint16
C16                 1000001 non-null uint16
C17                 1000001 non-null uint16
C18                 1000001 non-null uint16
C19                 1000001 non-null uint16
C20                 1000001 non-null uint16
C21                 1000001 non-null uint16
dtypes: bool(1), datetime64[ns](1), object(10), uint16(12)
memory usage: 107.8+ MB
```

Part 1: Exploratory Data Analytics

In [18]:

```
train_data.describe()
```

Out[18]:

	C1	banner_pos	device_type	device_conn_type	C14	C15	C16	
count	1.000001e+06	1.000001e+06	1.000001e+06	1.000001e+06	1.000001e+06	1.000001e+06	1.000001e+06	1.000
mean	1.004967e+03	2.879897e-01	1.015556e+00	3.314447e-01	1.884572e+04	3.189284e+02	6.009973e+01	2.113

	C1	banner_pos	device_type	device_conn_type	C14	C15	C16	
std	1.095126e+00	5.071704e-01	5.291616e-01	8.550856e-01	4.950229e+03	2.146769e+01	4.729728e+01	6.086
min	1.001000e+03	0.000000e+00	0.000000e+00	0.000000e+00	3.750000e+02	1.200000e+02	2.000000e+01	1.120
25%	1.005000e+03	0.000000e+00	1.000000e+00	0.000000e+00	1.692000e+04	3.200000e+02	5.000000e+01	1.863
50%	1.005000e+03	0.000000e+00	1.000000e+00	0.000000e+00	2.034600e+04	3.200000e+02	5.000000e+01	2.323
75%	1.005000e+03	1.000000e+00	1.000000e+00	0.000000e+00	2.189400e+04	3.200000e+02	5.000000e+01	2.526
max	1.012000e+03	7.000000e+00	5.000000e+00	5.000000e+00	2.405200e+04	1.024000e+03	1.024000e+03	2.758

In [20]:

```
train_data.head()
```

Out[20]:

	id	click	hour	C1	banner_pos	site_id	site_domain	site_category	app_id	app_domai
0	10010966574628106108	True	2014-10-21	1005	0	85f751fd	c4e18dd6	50e219e0	0acbeaa3	45a51db4
1	10018563981679953217	False	2014-10-21	1005	0	85f751fd	c4e18dd6	50e219e0	8bfb92e0	7801e8d9
2	10030228488972929850	False	2014-10-21	1005	0	1fbe01fe	f3845767	28905ebd	ecad2386	7801e8d9
3	10031998322520623865	False	2014-10-21	1005	0	6c5b482c	7687a86e	3e814130	ecad2386	7801e8d9
4	10032235721168274495	False	2014-10-21	1005	0	1fbe01fe	f3845767	28905ebd	ecad2386	7801e8d9

5 rows × 24 columns

In [23]:

```
train_data.iloc[:, :24].head(5)

'''
24 features encompassing site attributes, application features, device attributes

Target features - click
>>C14 - C21 - Anonymized categorical variables

Features kept anonymous via. md5 hashing encrypton :

>>Site features - Site_id, Site_domain, Site_category
>>App features - app_id, app_domain
>>Device features - device_type, device_conn_type

'''
```

Out[23]:

	id	click	hour	C1	banner_pos	site_id	site_domain	site_category	app_id	app_domai
0	10010966574628106108	True	2014-10-21	1005	0	85f751fd	c4e18dd6	50e219e0	0acbeaa3	45a51db4
1	10018563981679953217	False	2014-10-21	1005	0	85f751fd	c4e18dd6	50e219e0	8bfb92e0	7801e8d9
2	10030228488972929850	False	2014-10-21	1005	0	1fbe01fe	f3845767	28905ebd	ecad2386	7801e8d9
3	10031998322520623865	False	2014-10-21	1005	0	6c5b482c	7687a86e	3e814130	ecad2386	7801e8d9
4	10032235721168274495	False	2014-10-21	1005	0	1fbe01fe	f3845767	28905ebd	ecad2386	7801e8d9

5 rows × 24 columns

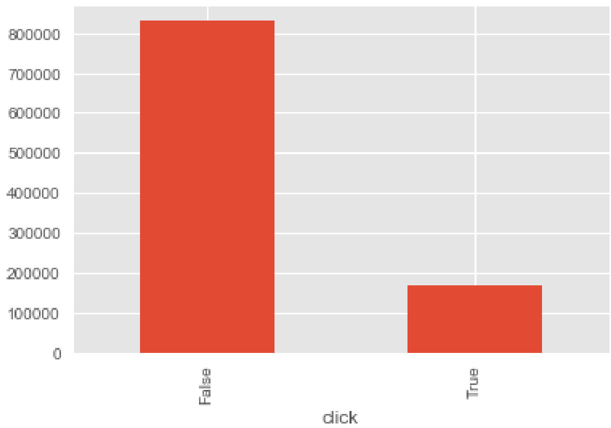
CTR analysis ~ Click v/s No click distribution

In [32]:

```
%matplotlib inline

train_data.groupby('click').size().plot(kind = 'bar')
rows = train_data.shape[0]

click_through_rate = train_data['click'].value_counts()/rows

click_through_rate

'''
'''
```

Out[32]:

```
False    0.830052
True     0.169948
Name: click, dtype: float64
```



Click through rate on a set of 1 million records of click stream data sampled at random from the population of 40 million records is 16.9 ~ 17%. CTR effectively = 17%

Feature Engineering

Studying the relationships between different features and the target variable i.e 'Click'. Manipulating data in the process, introducing new metrics

HOUR

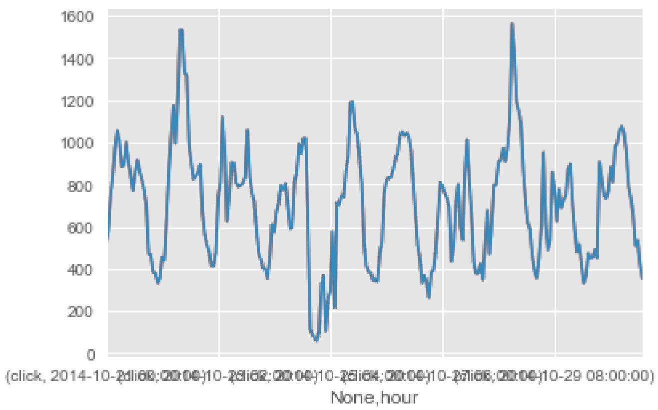
In [308]:

```
'''
Metric 1. HOUR
'''

train_data.hour.describe()


'''INSIGHT 2: Impressions V/S Clicks
    MAXIMUM number of Impresisons around 1 P.M ~ 1561 '''

df_impressions = train_data.groupby('hour').agg({'click':'sum'})
#df_impressions
df_impressions.unstack().plot()
```

```
df_click = train_data[train_data['click']==1]
temp_click = df_click.groupby('hour').agg({'click' : 'sum'})
temp_click.unstack().plot()

#temp_click
```

Out[308]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20bae7d16a0>
```



In [309]:

```
train_data.hour.describe()
```

Out[309]:

```
count                 1000001
unique                    240
top       2014-10-22 09:00:00
freq                    10909
first     2014-10-21 00:00:00
last      2014-10-30 23:00:00
Name: hour, dtype: object
```

In [ ]:

```
#Since Time Features are thought of in terms of cycles
```

Creating Metrics From The Hour Field

In [115]:

```
''' HOUR as a metric is difficult to read because it is a time stamp
    Introducing new metrics:
     1. hour_in_day - Better KPI to assess the impressions v/s clicks behavior w.r.t hour in day
     2. weekday -- To study user behavior w.r.t clicks on each day
     3. Day_name -- To extract the day name from the HOUR feature for a better understanding
'''

train_data['hour_in_day'] = train_data['hour'].apply(lambda val : val.hour)
#train_data_clicks['hour_in_day'] = train_data_clicks['hour'].apply(lambda val : val.hour)

train_data['weekday'] = train_data['hour'].apply(lambda val: val.dayofweek)
#train_data_clicks['weekday'] = train_data_clicks['hour'].apply(lambda val: val.dayofweek)

train_data['day_name'] = train_data['hour'].apply(lambda x: x.strftime('%A'))
#train_data_clicks['day_name'] = train_data_clicks['hour'].apply(lambda x: x.strftime('%A'))
```

In [71]:

```
train_data.columns
```

Out[71]:

```
Index(['id', 'click', 'hour', 'C1', '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', 'C14',
       'C15', 'C16', 'C17', 'C18', 'C19', 'C20', 'C21', 'hour_in_day',
       'weekday', 'day_name'],
      dtype='object')
```

Hour In day, weekday and day_name columns added

Monday = 0, Sunday = 6

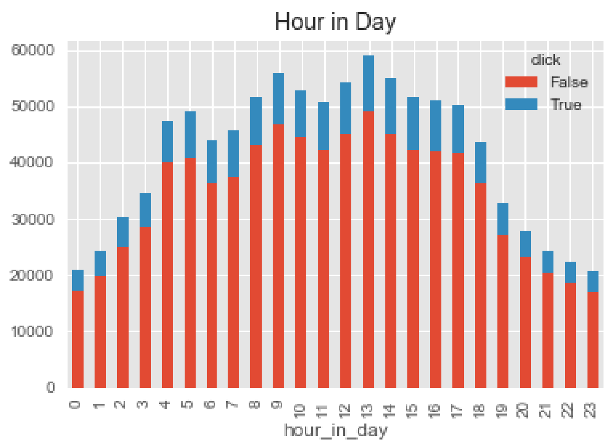
HOUR IN DAY

In [73]:

```
#train_data['hour_in_day'].nunique() ~ 0 TO 23
train_data.groupby(['hour_in_day', 'click']).size().unstack().plot(kind='bar', stacked=True, title="Hou
r in Day")
```

Out[73]:

```
'\ntrain_data[\'weekday\'].nunique()\ntrain_data.groupby([\'weekday\', \'click\']).size().unstack().plo
t(kind=\'bar\', stacked=True, title="Days of the week")\n'
```



In [76]:

```
train_data[['hour','click']].groupby(['hour']).sum().sort_values('click',ascending=False)
```

Out[76]:

	click
hour	
2014-10-28 13:00:00	1561
2014-10-22 09:00:00	1534
2014-10-22 10:00:00	1532
2014-10-28 14:00:00	1416
2014-10-22 11:00:00	1331
2014-10-22 12:00:00	1319
2014-10-22 08:00:00	1212
2014-10-28 15:00:00	1193
2014-10-25 14:00:00	1191

hour	click
2014-10-25 13:00:00	[illegible]
2014-10-22 06:00:00	1175
2014-10-28 16:00:00	1149
2014-10-23 04:00:00	1119
2014-10-28 12:00:00	1114
2014-10-28 17:00:00	1088
2014-10-30 14:00:00	1076
2014-10-25 15:00:00	1070
2014-10-30 13:00:00	1059
2014-10-23 15:00:00	1058
2014-10-21 05:00:00	1056
2014-10-26 12:00:00	1050
2014-10-26 14:00:00	1044
2014-10-30 15:00:00	1041
2014-10-25 16:00:00	1038
2014-10-26 11:00:00	1034
2014-10-26 13:00:00	1033
2014-10-26 15:00:00	1031
2014-10-22 05:00:00	1027
2014-10-24 17:00:00	1020
2014-10-24 16:00:00	1018
...	...
2014-10-25 22:00:00	380
2014-10-27 21:00:00	379
2014-10-27 22:00:00	379
2014-10-21 22:00:00	378
2014-10-25 01:00:00	370
2014-10-26 22:00:00	369
2014-10-29 22:00:00	364
2014-10-29 00:00:00	355
2014-10-30 23:00:00	354
2014-10-24 00:00:00	353
2014-10-26 00:00:00	350
2014-10-22 00:00:00	350
2014-10-28 00:00:00	348
2014-10-25 23:00:00	345
2014-10-26 01:00:00	339
2014-10-26 23:00:00	337
2014-10-21 23:00:00	333
2014-10-29 21:00:00	333
2014-10-26 21:00:00	331
2014-10-25 00:00:00	325
2014-10-25 04:00:00	298
2014-10-27 00:00:00	264
2014-10-25 03:00:00	249

	click
2014-10-25 06:00:00	216
2014-10-24 19:00:00	115
2014-10-25 02:00:00	104
2014-10-24 23:00:00	102
2014-10-24 20:00:00	88
2014-10-24 21:00:00	72
2014-10-24 22:00:00	57

240 rows × 1 columns

In [82]:

```
train_data_clicks[['hour','click']].groupby(['hour']).sum().sort_values('click',ascending=False)
```

Out[82]:

	click
hour	
2014-10-28 13:00:00	1561
2014-10-22 09:00:00	1534
2014-10-22 10:00:00	1532
2014-10-28 14:00:00	1416
2014-10-22 11:00:00	1331
2014-10-22 12:00:00	1319
2014-10-22 08:00:00	1212
2014-10-28 15:00:00	1193
2014-10-25 14:00:00	1191
2014-10-25 13:00:00	1186
2014-10-22 06:00:00	1175
2014-10-28 16:00:00	1149
2014-10-23 04:00:00	1119
2014-10-28 12:00:00	1114
2014-10-28 17:00:00	1088
2014-10-30 14:00:00	1076
2014-10-25 15:00:00	1070
2014-10-30 13:00:00	1059
2014-10-23 15:00:00	1058
2014-10-21 05:00:00	1056
2014-10-26 12:00:00	1050
2014-10-26 14:00:00	1044
2014-10-30 15:00:00	1041
2014-10-25 16:00:00	1038
2014-10-26 11:00:00	1034
2014-10-26 13:00:00	1033
2014-10-26 15:00:00	1031
2014-10-22 05:00:00	1027
2014-10-24 17:00:00	1020
2014-10-24 16:00:00	1018

hour	click
...	...
2014-10-25 22:00:00	380
2014-10-27 21:00:00	379
2014-10-27 22:00:00	379
2014-10-21 22:00:00	378
2014-10-25 01:00:00	370
2014-10-26 22:00:00	369
2014-10-29 22:00:00	364
2014-10-29 00:00:00	355
2014-10-30 23:00:00	354
2014-10-24 00:00:00	353
2014-10-26 00:00:00	350
2014-10-22 00:00:00	350
2014-10-28 00:00:00	348
2014-10-25 23:00:00	345
2014-10-26 01:00:00	339
2014-10-26 23:00:00	337
2014-10-21 23:00:00	333
2014-10-29 21:00:00	333
2014-10-26 21:00:00	331
2014-10-25 00:00:00	325
2014-10-25 04:00:00	298
2014-10-27 00:00:00	264
2014-10-25 03:00:00	249
2014-10-25 06:00:00	216
2014-10-24 19:00:00	115
2014-10-25 02:00:00	104
2014-10-24 23:00:00	102
2014-10-24 20:00:00	88
2014-10-24 21:00:00	72
2014-10-24 22:00:00	57

240 rows × 1 columns

Hour in day - CTR v/s impressions analysis

In [108]:

```
hour_df = pd.DataFrame()

#creating a new independendt data frame
```

In [110]:

```
hour_df['hr'] = train_data_clicks[['hour_in_day','click']].groupby(['hour_in_day']).count().reset_index
().sort_values('click',ascending=False)['hour_in_day']

hour_df
#hour_dataframe.drop("hr", axis = 1, inplace = True)

#train_data_clicks.head()
```

```
#train_data_clicks.head()
```

Out[110]:

	hr
13	13
14	14
15	15
12	12
16	16
9	9
11	11
17	17
8	8
10	10
7	7
5	5
6	6
4	4
18	18
3	3
19	19
2	2
1	1
20	20
21	21
0	0
22	22
23	23

Hour in day - Clicks

In [112]:

```
'''
Taking into account just the CLICKS
'''
hour_df['pos_clicks'] = train_data_clicks[['hour_in_day','click']]\
                        .groupby(['hour_in_day']).count()\
                        .reset_index()\
                        .sort_values('click',ascending=False)['click']

hour_df
```

Out[112]:

	hr	pos_clicks
13	13	9893
14	14	9845
15	15	9459
12	12	9232
16	16	9170

	hr	pos_clicks
9	9	8978
11	11	8626
17	17	8617
8	8	8573
10	10	8456
7	7	8215
5	5	8059
6	6	7521
4	4	7460
18	18	7304
3	3	5996
19	19	5438
2	2	5246
1	1	4473
20	20	4428
21	21	3972
0	0	3723
22	22	3694
23	23	3570

Hour in day - Impressions

In [117]:

```
'''
Taking into account the IMPRESSIONS
'''
hour_df['impressions_total'] = train_data[['hour_in_day','click']]\
                            .groupby(['hour_in_day']).count()\
                            .reset_index()\
                            .sort_values('click',ascending=False)['click']

hour_df
```

Out[117]:

	hr	pos_clicks	impressions_total
13	13	9893	58886
14	14	9845	54974
15	15	9459	51764
12	12	9232	54308
16	16	9170	50996
9	9	8978	55822
11	11	8626	50843
17	17	8617	50342
8	8	8573	51738
10	10	8456	52845
7	7	8215	45708
5	5	8059	48991
6	6	7521	43924

	hr	pos_clicks	impressions_total
4	4	7460	47500
18	18	7304	43606
3	3	5996	34617
19	19	5438	32723
2	2	5246	30218
1	1	4473	24385
20	20	4428	27748
21	21	3972	24283
0	0	3723	20938
22	22	3694	22344
23	23	3570	20498

Introducing Click through rate

In [129]:

```
'''
Introducing a new feature click through rate
'''

hour_df['click_through_rate'] = 100*hour_df['pos_clicks']/hour_df['impressions_total']

#hour_df.sort_values(ascending = False, by = 'impressions_total')
hour_df.sort_values(ascending = False, by = 'click_through_rate')
```

Out[129]:

	hr	pos_clicks	impressions_total	click_through_rate
1	1	4473	24385	18.343244
15	15	9459	51764	18.273317
16	16	9170	50996	17.981802
7	7	8215	45708	17.972784
14	14	9845	54974	17.908466
0	0	3723	20938	17.781068
23	23	3570	20498	17.416333
2	2	5246	30218	17.360514
3	3	5996	34617	17.320969
6	6	7521	43924	17.122757
17	17	8617	50342	17.116920
12	12	9232	54308	16.999337
11	11	8626	50843	16.965954
13	13	9893	58886	16.800258
18	18	7304	43606	16.749989
19	19	5438	32723	16.618281
8	8	8573	51738	16.570026
22	22	3694	22344	16.532402
5	5	8059	48991	16.449960
21	21	3972	24283	16.357122
9	9	8978	55822	16.083265

	hr	pos_clicks	impressions_total	click_through_rate
10	10	8456	52845	16.001514
20	20	4428	27748	15.957907
4	4	7460	47500	15.705263

In [130]:

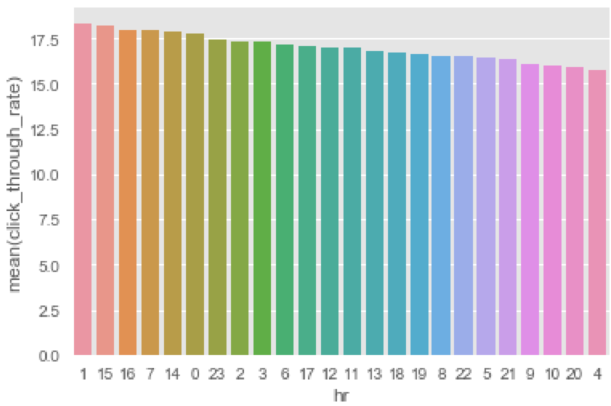
```
list_of_hours = hour_df.sort_values(by='click_through_rate',ascending=False)['hr'].tolist()
```

In [133]:

```
import seaborn as sns
sns.barplot(y='click_through_rate',x='hr'\
            ,data=hour_df\
            ,order=list_of_hours)
```

Out[133]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20a804bc400>
```



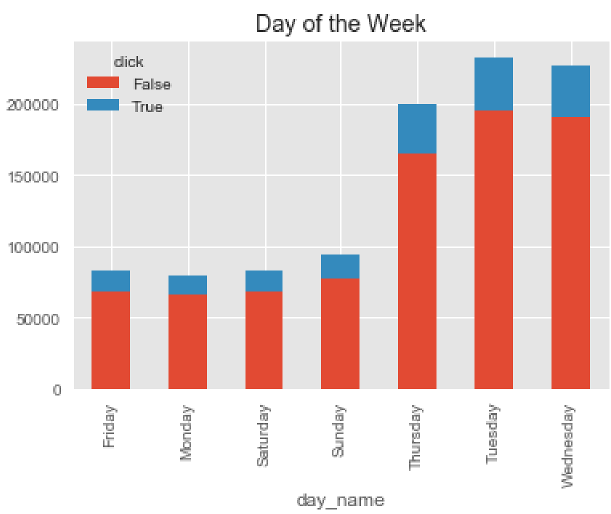
Weekday ~ day_name

In [135]:

```
train_data.groupby(['day_name','click']).size().unstack().plot(kind='bar', stacked=True, title="Day of the Week")
```

Out[135]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20b3634a828>
```



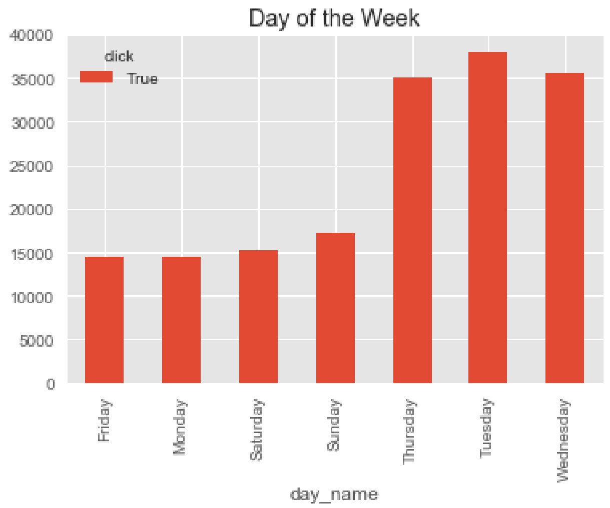
weekday ~ day_name (for clicks)

In [136]:

```
train_data_clicks.groupby(['day_name','click']).size().unstack().plot(kind='bar', stacked=True, title="
Day of the Week")
```

Out[136]:

<matplotlib.axes._subplots.AxesSubplot at 0x20b363574e0>



In [138]:

```
train_data_clicks[['day_name','click']].groupby(['day_name']).count().sort_values('click',ascending=Fal
se)
```

Out[138]:

	click
day_name	
Tuesday	38050
Wednesday	35635
Thursday	35051
Sunday	17250
Saturday	15107
Monday	14489
Friday	14366

Most clicks on Tuesday, then wednesday followed by Thursday

Day wise analysis of click through rates

In [140]:

```
day_df = pd.DataFrame()
```

In [141]:

```
day_df['day'] = train_data_clicks[['day_name','click']]\
                        .groupby(['day_name']).count()\
                        .reset_index()\
                        .sort_values('click',ascending=False)['day_name']
```

```
                               .sort_values('click',ascending=False)['day_name']
day_df
```

Out[141]:

	day
5	Tuesday
6	Wednesday
4	Thursday
3	Sunday
2	Saturday
1	Monday
0	Friday

Day-wise clicks

In [142]:

```
day_df['pos_clicks'] = train_data_clicks[['day_name','click']]\
                               .groupby(['day_name']).count()\
                               .reset_index()\
                               .sort_values('click',ascending=False)['click']
day_df
```

Out[142]:

	day	pos_clicks
5	Tuesday	38050
6	Wednesday	35635
4	Thursday	35051
3	Sunday	17250
2	Saturday	15107
1	Monday	14489
0	Friday	14366

Day-wise Impressions

In [146]:

```
day_df['total_impressions'] = train_data[['day_name','click']]\
                                        .groupby(['day_name']).count()\
                                        .reset_index()\
                                        .sort_values('click',ascending=False)['click']
day_df
```

Out[146]:

	day	pos_clicks	total_impressions	click_pct
5	Tuesday	38050	232962	100.0
6	Wednesday	35635	227003	100.0
4	Thursday	35051	199970	100.0
3	Sunday	17250	94459	100.0
2	Saturday	15107	83079	100.0
1	Monday	14489	79938	100.0

	day	pos_clicks	total_impressions	click_pct
1	Monday	14489	79938	100.0
0	Friday	14366	82590	100.0

Day-wise Click Percentages

In [148]:

```
day_df['click_pct'] = 100*day_df['pos_clicks']/day_df['total_impressions']
day_df.sort_values(ascending = False, by = 'click_pct')
```

Out[148]:

	day	pos_clicks	total_impressions	click_pct
3	Sunday	17250	94459	18.261891
2	Saturday	15107	83079	18.183897
1	Monday	14489	79938	18.125297
4	Thursday	35051	199970	17.528129
0	Friday	14366	82590	17.394358
5	Tuesday	38050	232962	16.333136
6	Wednesday	35635	227003	15.698030

Sunday has the highest value of click through rate

In [150]:

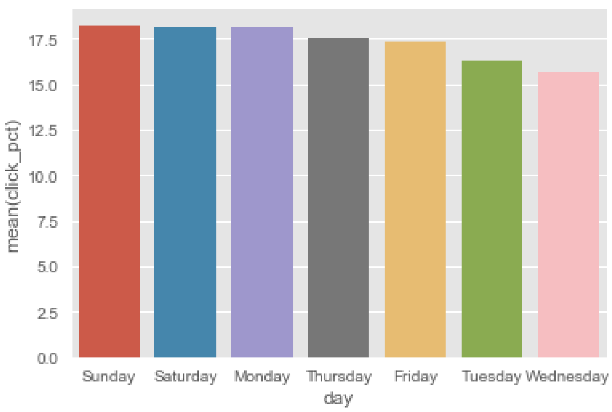
```
list_of_days = day_df.sort_values(by='click_pct',ascending=False)['day'].tolist()
```

In [151]:

```
sns.barplot(y='click_pct',x='day'\
            ,data=day_df\
            ,order=list_of_days)
```

Out[151]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20a82b64cf8>
```



Banner Position

Banner positions representing attractive and appealing designs that might highly affect a user's behavior and in turn trigger their decision to click. Or not. Hence making it an effective metric to predict clicks

In [310]:

```
train_data['banner_pos'].unique()
```

Out[310]:

```
array([0, 1, 5, 2, 4, 7, 3], dtype=uint64)
```

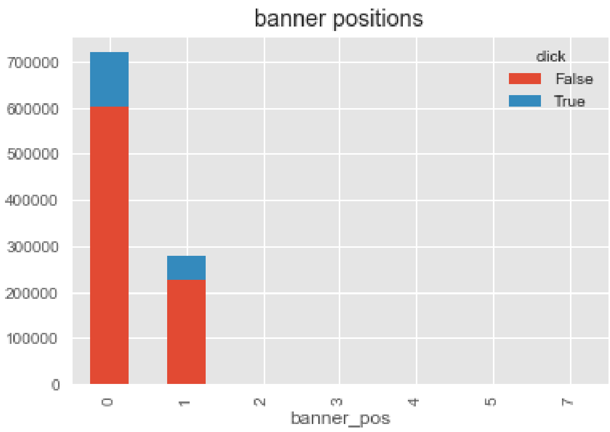
It's unclear as to what the 7 banner positions (represented as integers) represent. Intuitively and based on research, the 7 positions might represent ad placing in a 2D webpage

In [152]:

```
banner_temp =train_data[['banner_pos','click']].groupby(['banner_pos','click'])

banner_temp.size().unstack().plot(kind='bar',stacked=True, title='banner positions')
```

Out[152]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20a82c699e8>
```



Positions 0 and 1 ~ the most prominent banner positions garnering most impressions

In [153]:

```
train_data[['banner_pos','click']].groupby(['banner_pos']).count().sort_values('click',ascending=False)
```

Out[153]:

	click
banner_pos	
0	720202
1	277965
7	1086
2	338
4	197
5	160
3	53

BANNER POSITIONS 0 and 1 generating most impressions and clicks

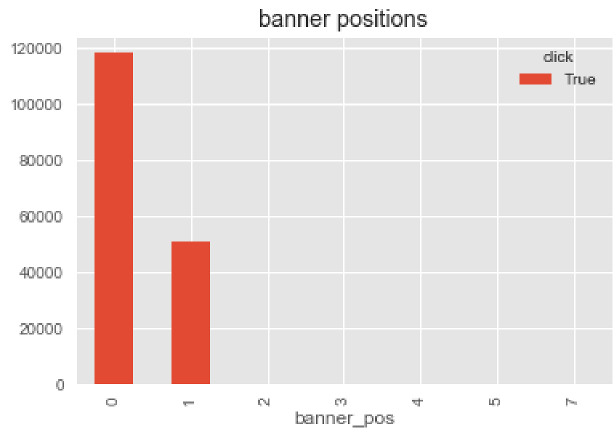
In [154]:

```
banner_temp =train_data_clicks[['banner_pos','click']].groupby(['banner_pos','click'])
```

```
banner_temp.size().unstack().plot(kind='bar',stacked=True, title='banner positions')
```

Out[154]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20b1bb42dd8>
```



In [155]:

```
train_data_clicks[['banner_pos','click']].groupby(['banner_pos']).count().sort_values('click',ascending
=False)
```

Out[155]:

	click
banner_pos	
0	118482
1	50998
7	358
2	44
4	39
5	18
3	9

CTR analysis on Banner position

In [157]:

```
import pandas as pd

banner_df = pd.DataFrame()
```

In [158]:

```
banner_df['position'] = train_data_clicks[['banner_pos','click']]\
                        .groupby(['banner_pos']).count()\
                        .reset_index()\
                        .sort_values('click',ascending=False)['banner_pos']
```

In [159]:

```
banner_df['pos_clicks'] = train_data_clicks[['banner_pos','click']]\
                        .groupby(['banner_pos']).count()\
                        .reset_index()\
                        .sort_values('click',ascending=False)['click']
```

In [160]:

```
banner_df['total_impressions'] = train_data[['banner_pos','click']]\
                                .groupby(['banner_pos']).count()\
                                .reset_index()\
                                .sort_values('click',ascending=False)['click']
```

In [162]:

```
banner_df['click_pct'] = 100*banner_df['pos_clicks']/banner_df['total_impressions']

banner_df
```

Out[162]:

	position	pos_clicks	total_impressions	click_pct
0	0	118482	720202	16.451218
1	1	50998	277965	18.346914
6	7	358	1086	32.965009
2	2	44	338	13.017751
4	4	39	197	19.796954
5	5	18	160	11.250000
3	3	9	53	16.981132

In [163]:

```
banner_df.sort_values(ascending=False,by='click_pct')
```

Out[163]:

	position	pos_clicks	total_impressions	click_pct
6	7	358	1086	32.965009
4	4	39	197	19.796954
1	1	50998	277965	18.346914
3	3	9	53	16.981132
0	0	118482	720202	16.451218
2	2	44	338	13.017751
5	5	18	160	11.250000

Banner 7 has the highest click through rate

In [164]:

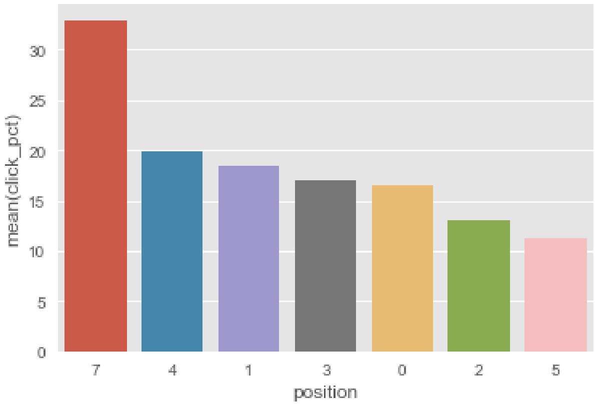
```
list_of_banners = banner_df.sort_values(by='click_pct',ascending=False)['position'].tolist()
```

In [165]:

```
sns.barplot(y='click_pct',x='position'\
            ,data=banner_df\
            ,order=list_of_banners)
```

Out[165]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20b1bbe2860>
```



Banner position 7 seems to be a nice choice for placing advertisements. As per click through rate.

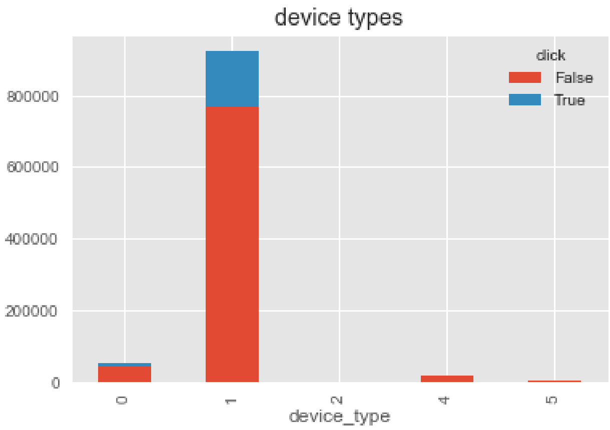
DEVICE TYPE Metrics

In [166]:

```
device_temp = train_data[['device_type','click']].groupby(['device_type','click'])

device_temp.size().unstack().plot(kind='bar',stacked=True, title='device types')
```

Out[166]:

<matplotlib.axes._subplots.AxesSubplot at 0x20b1ba86c18>



Device type 1 getting most impressions among the 5 devices

In [167]:

```
train_data[['device_type','click']].groupby(['device_type']).count().sort_values('click',ascending=Fals
e)
```

Out[167]:

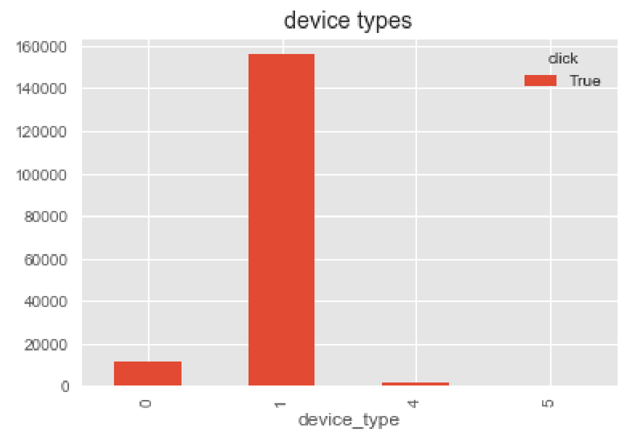
	click
device_type	
1	922389
0	55135
4	19214
5	3262
2	1

In [168]:

```
train_data_clicks[['device_type','click']].groupby(['device_type','click']).size().unstack().plot(kind=
'bar',stacked=True, title='device types')
```

Out[168]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20b1be01ef0>
```



In [169]:

```
train_data_clicks[['device_type','click']].groupby(['device_type']).count().sort_values('click',ascendi
ng=False)
```

Out[169]:

	click
device_type	
1	156143
0	11707
4	1777
5	321

Device Type 1 gets the maximum number of clicks too

In [201]:

```
device1_df = train_data_clicks[train_data_clicks['device_type']==1]

# extract CLICKS for DEVICE TYPE 1
```

Hourly distribution of clicks on Device 1

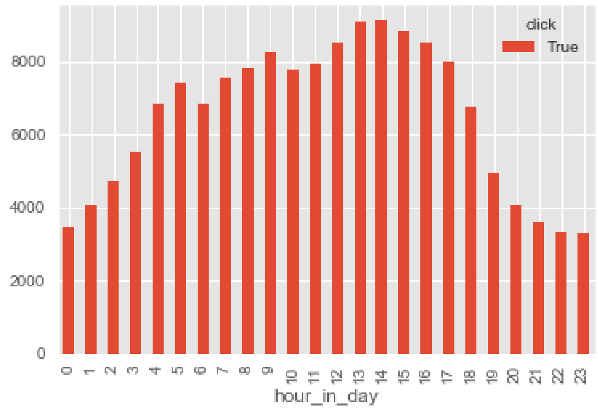
In [204]:

```
temp_device_df = device1_df.groupby(['hour_in_day', 'click'])

temp_device_df.size().unstack().plot(kind='bar', stacked=True, title="Clicks spread across hour in day
for Device 1")
```

Out[204]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20b1de2ea58>
```

Clicks spread across hour in day for Device 1



'''Device type 1 --- probably cell phone// Desktop Reasons --- Businesses might not prefer showing ads later in the evening----- after work hours// business hours (Click spread max between 9 to 5)

Click through rate analysis w.r.t Device type(merging data frames)

Had to merge data frames to ensure consistency

In [179]:

```
import pandas as pd
dev_type_df=pd.DataFrame()

dev_type_df_total_imp = pd.DataFrame()
```

In [184]:

```
#TOTAL CLICKS

dev_type_df = train_data_clicks.groupby('device_type').agg({'click':'sum'}).reset_index()

dev_type_df
```

Out[184]:

	device_type	click
0	0	11707.0
1	1	156143.0
2	4	1777.0
3	5	321.0

In [185]:

```
#TOTAL IMPRESSIONS

dev_type_df_total_imp = train_data.groupby('device_type').agg({'click':'count'}).reset_index()
```

Out[185]:

	device_type	click
0	0	55135
1	1	922389
2	2	1
3	4	19214

4	device_type 5	3262 click

In [183]:

```
#dev_type_df_total_imp.drop([2], inplace = True)

dev_type_df_total_imp
```

Out[183]:

	device_type	click
0	0	55135
1	1	922389
3	4	19214
4	5	3262

In [187]:

```
dev_type_df['total_impressions'] = dev_type_df_total_imp['click']

dev_type_df
```

Out[187]:

	device_type	click	total_impressions
0	0	11707.0	55135
1	1	156143.0	922389
2	4	1777.0	1
3	5	321.0	19214

In [189]:

```
## sucess percentage == CTR

dev_type_df['success_pct'] = (dev_type_df['click']/dev_type_df['total_impressions'])*100

dev_type_df
```

Out[189]:

	device_type	click	total_impressions	success_pct
0	0	11707.0	55135	21.233336
1	1	156143.0	922389	16.928107
2	4	1777.0	1	177700.000000
3	5	321.0	19214	1.670657

In [191]:

```
dev_type_df_total_imp.columns = ['device_type', 'click2']

merged_df = pd.merge(left = dev_type_df , right = dev_type_df_total_imp,
                     how = 'inner', on = 'device_type')
```

In [192]:

```
merged_df
```

Out[192]:

	device_type	click	total_impressions	success_pct	click2
0	0	11707.0	55135	21.233336	55135
1	1	156143.0	922389	16.928107	922389
2	4	1777.0	1	177700.000000	19214
3	5	321.0	19214	1.670657	3262

del merged_df['total_impressions']

merged_df.columns = ['device_type', 'click','success_pct', 'total_impressions'] merged_df

In [200]:

```
merged_df['success_pct'] = 100*(merged_df['click']/merged_df['total_impressions'])

merged_df
```

Out[200]:

	device_type	click	success_pct	total_impressions
0	0	11707.0	21.233336	55135
1	1	156143.0	16.928107	922389
2	4	1777.0	9.248465	19214
3	5	321.0	9.840589	3262

Device Type 0 with the highest click through rate

App Related Metrics

App_Id, App_Domain, App_Category

In [206]:

```
app_features = ['app_id', 'app_domain', 'app_category']
```

In [207]:

```
train_data.groupby('app_category').agg({'click':'sum'}).sort_values(by='click',ascending = False)
```

Out[207]:

	click
app_category	
07d7df22	129085.0
0f2161f8	25441.0
f95efa07	6987.0
cef3e649	4018.0
8ded1f7a	3326.0
d1327cf5	351.0
09481d60	224.0

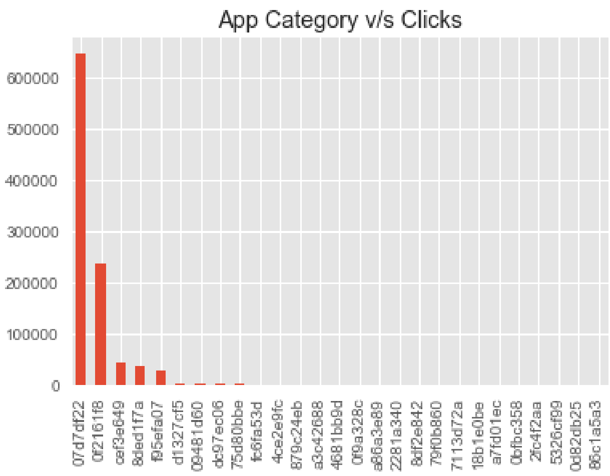
app_category	click
dc97ec06	108.0
75d80bbe	101.0
4ce2e9fc	68.0
879c24eb	41.0
fc6fa53d	33.0
0f9a328c	20.0
4681bb9d	19.0
a3c42688	14.0
a86a3e89	11.0
8df2e842	7.0
79f0b860	1.0
7113d72a	1.0
18b1e0be	1.0
0bfbc358	1.0
86c1a5a3	0.0
2fc4f2aa	0.0
2281a340	0.0
a7fd01ec	0.0
5326cf99	0.0
0d82db25	0.0

In [208]:

```
train_data['app_category'].value_counts().plot(kind='bar', title='App Category v/s Clicks')
```

Out[208]:

<matplotlib.axes._subplots.AxesSubplot at 0x20b1fa3eef0>



Studying Clicks behavior across different app categories

In [211]:

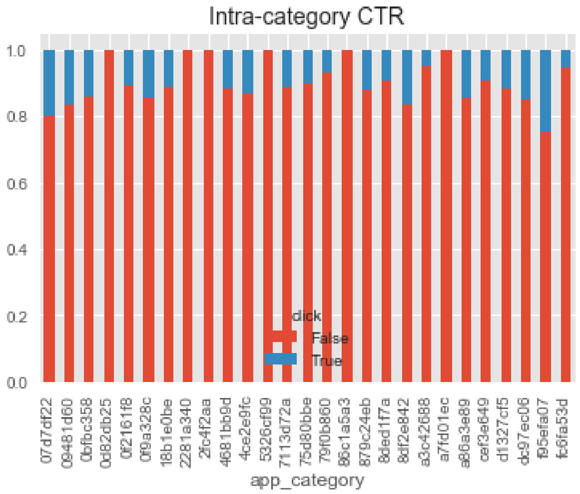
```
train_app_category = train_data.groupby(['app_category', 'click']).size().unstack()
```

In [212]:

```
train_app_category.div(train_app_category.sum(axis=1), axis=0).plot(kind='bar', stacked=True, title="In
tra-category CTR")
```

Out[212]:

<matplotlib.axes._subplots.AxesSubplot at 0x20b22ddb5f8>



C1, C14-C21 features

In [213]:

```
features = ['C1', 'C14', 'C15', 'C16', 'C17', 'C18',
            'C20', 'C21']

train_data[features].astype('object').describe()
```

Out[213]:

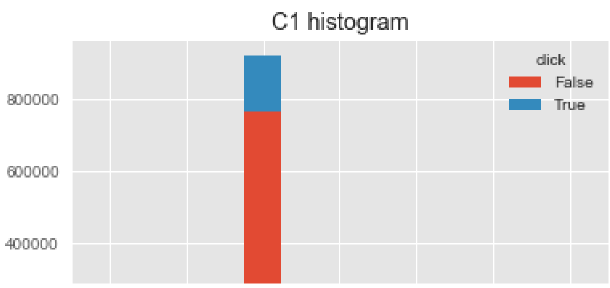
	C1	C14	C15	C16	C17	C18	C20	C21
count	1000001	1000001	1000001	1000001	1000001	1000001	1000001	1000001
unique	7	2251	8	9	420	4	163	60
top	1005	4687	320	50	1722	0	65535	23
freq	918405	23298	932737	943504	111786	419161	467791	220235

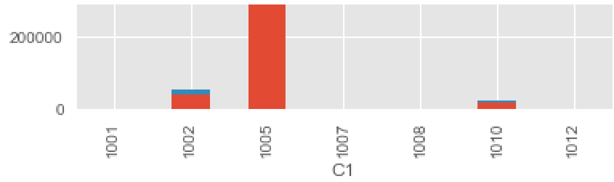
In [214]:

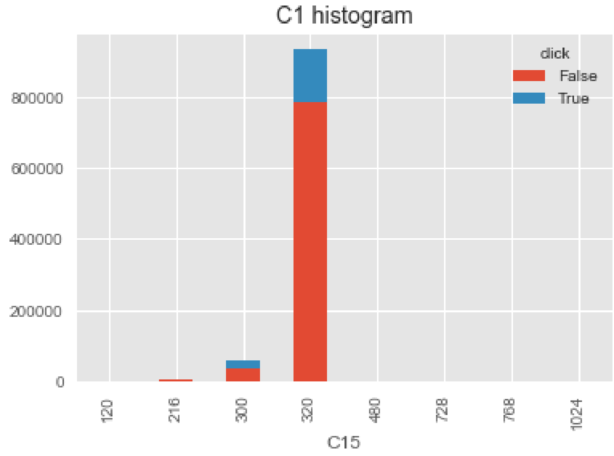
```
train_data.groupby(['C1', 'click']).size().unstack().plot(kind='bar', stacked=True, title='C1 histogram
')
train_data.groupby(['C15', 'click']).size().unstack().plot(kind='bar', stacked=True, title='C1 histogra
m')
train_data.groupby(['C16', 'click']).size().unstack().plot(kind='bar', stacked=True, title='C1 histogra
m')
train_data.groupby(['C18', 'click']).size().unstack().plot(kind='bar', stacked=True, title='C1 histogra
m')
```

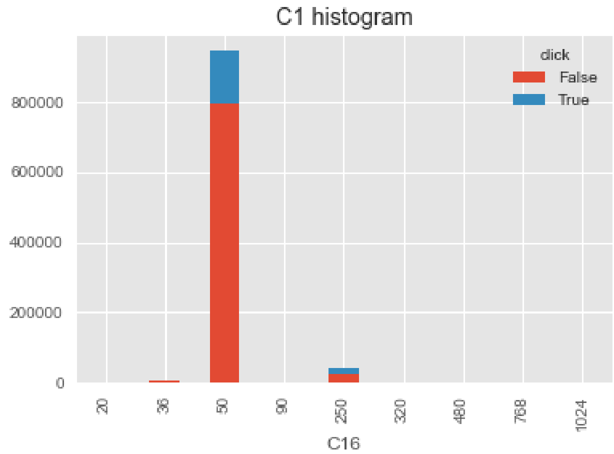
Out[214]:

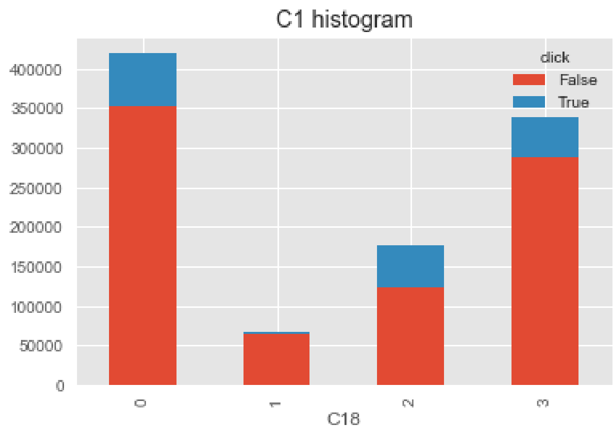
<matplotlib.axes._subplots.AxesSubplot at 0x20b27fe9588>











Part 2: Developing the Prediction model

Using the key metrics discussed above as a part of the EDA to put together a predictive model in order to forecast Clicks

Data preparation stage ~~ To be fed in the data pipeline

In [314]:

```
model_features = ['weekday', 'hour_in_day',
                  'banner_pos', 'site_category',
                  'device_conn_type', 'app_category',
                  'device_type']
```

In [315]:

```
model_target = 'click'
```

In [ ]:

```
train_model = train_data[model_features+[model_target]].sample(frac=0.1,random_state=42)
```

Clubbing the model features with the target and selecting a fraction in order to speeden up computation

In [278]:

```
def one_hot_features(data_frame, feature_set):
    new_data_frame = pd.get_dummies(data_frame,
                                     columns = feature_set,
                                    sparse = True)

    return new_data_frame
```

Features Site_category and App_category are hashed and need to be represented in a readable format

Banner_pos is represented as integers hence we make use of one hot encoding to deal with all these features

In [ ]:

```
train_model = one_hot_features(train_model,
                                ['site_category',
                                 'app_category',
                                 'banner_pos'])
```

In [226]:

```
train_data.head()
```

Out[226]:

	id	click	hour	C1	banner_pos	site_id	site_domain	site_category	app_id	app_domai
0	10010966574628106108	True	2014-10-21	1005	0	85f751fd	c4e18dd6	50e219e0	0acbeaa3	45a51db4
1	10018563981679953217	False	2014-10-21	1005	0	85f751fd	c4e18dd6	50e219e0	8bfb92e0	7801e8d9
2	10030228488972929850	False	2014-10-21	1005	0	1fbe01fe	f3845767	28905ebd	ecad2386	7801e8d9
3	10031998322520623865	False	2014-10-21	1005	0	6c5b482c	7687a86e	3e814130	ecad2386	7801e8d9
4	10032235721168274495	False	2014-10-21	1005	0	1fbe01fe	f3845767	28905ebd	ecad2386	7801e8d9

5 rows × 27 columns

Extracting all columns from the train model except the target mask column

In [281]:

```
model_features = np.array(train_model.columns[train_model.columns!=model_target].tolist())
```

In [282]:

```
from sklearn.model_selection import train_test_split
```

In [283]:

```
#from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(
    train_model[model_features].values,
    train_model[model_target].values,
    test_size=0.3,
    random_state=42
)
```

Feature Selection ~ To reduce the dimensional space occupied and to deal with overfitting, use GRID SEARCH cross validation and regularization to obtain trade off b/w number of features and F-1 score

In [284]:

```
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import GridSearchCV

from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import SelectFromModel
from sklearn.metrics import f1_score
```

F1 score used as a performance metric because it represents the harmonic mean between precision and recall

In [285]:

```
num_splits = 3
c_values = np.logspace(-3,0,7)
```

In [286]:

```
stratified_k_fold = StratifiedKFold(n_splits=num_splits)

scores = np.zeros(7)
nr_params = np.zeros(7)
```

Model: logistic Regression with L1 regularization and balanced class weights

In [ ]:

```
for train_data, valid_data in stratified_k_fold.split(x_train,
                                                      y_train):
    for i, c in enumerate(np.logspace(-3, 0, 7)):
        lr_classify = LogisticRegression(penalty='l1',
                                         class_weight='balanced',
                                         C = c)
        lr_classify.fit(x_train[train_data],
                        y_train[train_data])

        #validation_Set evaluation

        y_prediction = lr_classify.predict(x_train[valid_data])
        score_f1 = f1_score(y_train[valid_data],
                            y_prediction, average='weighted' )

        scores[i] += score_f1 / num_splits

        ### spot the selected parameters ##
```

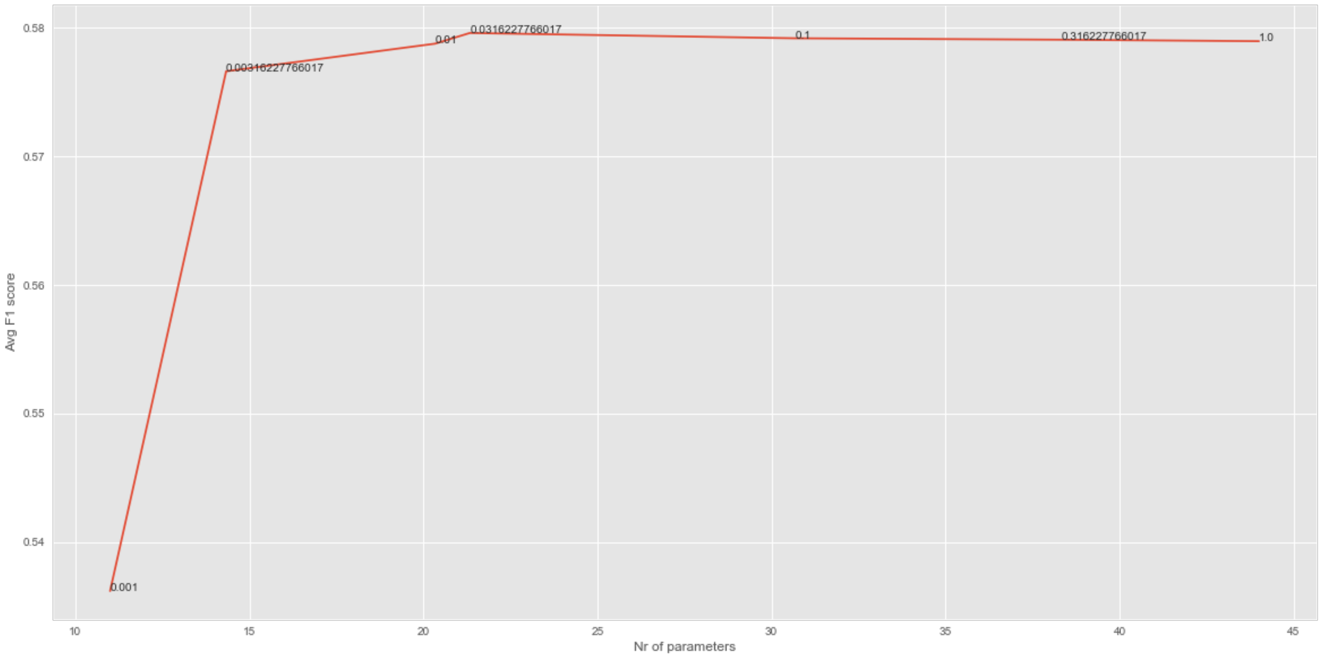
```
        ### spot the selected parameters ##

        model_selected = SelectFromModel(lr_classify, prefit=True)
        nr_params[i] += np.sum(model_selected.get_support()) / num_splits
```

In [254]:

```
plt.figure(figsize=(20, 10))
plt.plot(nr_params, scores)

for i, c in enumerate(c_values):
    plt.annotate(c, (nr_params[i], scores[i]))
plt.xlabel("Nr of parameters")
plt.ylabel("Avg F1 score")
```

Out[254]:

```
<matplotlib.text.Text at 0x20b2b047320>
```



Parameters obtained using c = 0.1 manage to reduce parameters dimension which optimizes the execution time also improving generalization capacity.

In [288]:

```
lr_classify = LogisticRegression(C=0.1, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l1', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
```

In [289]:

```
lr_classify.fit(x_train, y_train)
```

Out[289]:

```
LogisticRegression(C=0.1, class_weight='balanced', dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='ovr', n_jobs=1, penalty='l1', random_state=None,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False)
```

In [290]:

```
model_selected = SelectFromModel(lr_classify,
                                 prefit=True )
```

In [292]:

```
#pruned_params = model_selected.get_support()
pruned_params
```

Out[292]:

```
array([ True,  True,  True,  True,  True, False,  True,  True,  True,
       False,  True, False, False,  True, False, False,  True,  True,
       False, False, False, False,  True, False,  True, False,  True,
        True,  True,  True, False, False,  True, False, False, False,
       False, False,  True, False, False,  True, False, False, False,
        True, False,  True, False, False,  True,  True, False,  True,
        True,  True, False,  True, False, False,  True,  True], dtype=bool)
```

In [293]:

```
model_features = model_features[pruned_params]

x_train = x_train[:, pruned_params]

x_test = x_test[:, pruned_params]
```

Model : Gradient Boosting

Part 3: Evaluating results using various performance metrics

In [294]:

```
import xgboost
from xgboost import XGBClassifier
from sklearn.metrics import classification_report
```

In [295]:

```
x_train, x_valid, y_train, y_valid = train_test_split(
    x_train,
    y_train,
    stratify=y_train,
    test_size=0.1,
    random_state=42
)
```

In [318]:

```
model = XGBClassifier()
xgb_clf = model
```

Log Loss values measuring the performances of a classification models where the prediction label is a value between 0 and 1. The goal of the model is to minmize this value

In [297]:

```
xgb_clf.fit(x_train, y_train, early_stopping_rounds=10,
            eval_metric="logloss", eval_set=[(x_valid, y_valid)])
```

```
[0] validation_0-logloss:0.650231
Will train until validation_0-logloss hasn't improved in 10 rounds.
[1] validation_0-logloss:0.61528
[2] validation_0-logloss:0.586556
[3] validation_0-logloss:0.56279
[4] validation_0-logloss:0.543031
[5] validation_0-logloss:0.526546
[6] validation_0-logloss:0.512758
[7] validation_0-logloss:0.501204
```

```
[8] validation_0-logloss:0.491522
[9] validation_0-logloss:0.483386
[10] validation_0-logloss:0.476531
[11] validation_0-logloss:0.470792
[12] validation_0-logloss:0.465976
[13] validation_0-logloss:0.461713
[14] validation_0-logloss:0.458291
[15] validation_0-logloss:0.455468
[16] validation_0-logloss:0.453099
[17] validation_0-logloss:0.451071
[18] validation_0-logloss:0.449424
[19] validation_0-logloss:0.448046
[20] validation_0-logloss:0.446888
[21] validation_0-logloss:0.445896
[22] validation_0-logloss:0.445083
[23] validation_0-logloss:0.444377
[24] validation_0-logloss:0.443787
[25] validation_0-logloss:0.443308
[26] validation_0-logloss:0.44288
[27] validation_0-logloss:0.44253
[28] validation_0-logloss:0.4422
[29] validation_0-logloss:0.441958
[30] validation_0-logloss:0.441716
[31] validation_0-logloss:0.441526
[32] validation_0-logloss:0.441346
[33] validation_0-logloss:0.441176
[34] validation_0-logloss:0.44072
[35] validation_0-logloss:0.440597
[36] validation_0-logloss:0.440301
[37] validation_0-logloss:0.440208
[38] validation_0-logloss:0.440111
[39] validation_0-logloss:0.439798
[40] validation_0-logloss:0.439599
[41] validation_0-logloss:0.439502
[42] validation_0-logloss:0.439449
[43] validation_0-logloss:0.439405
[44] validation_0-logloss:0.439335
[45] validation_0-logloss:0.4393
[46] validation_0-logloss:0.439268
[47] validation_0-logloss:0.439116
[48] validation_0-logloss:0.439072
[49] validation_0-logloss:0.439018
[50] validation_0-logloss:0.438988
[51] validation_0-logloss:0.438959
[52] validation_0-logloss:0.438919
[53] validation_0-logloss:0.438886
[54] validation_0-logloss:0.438859
[55] validation_0-logloss:0.438836
[56] validation_0-logloss:0.438813
[57] validation_0-logloss:0.438782
[58] validation_0-logloss:0.438764
[59] validation_0-logloss:0.438691
[60] validation_0-logloss:0.43867
[61] validation_0-logloss:0.438655
[62] validation_0-logloss:0.438531
[63] validation_0-logloss:0.43851
[64] validation_0-logloss:0.438489
[65] validation_0-logloss:0.438477
[66] validation_0-logloss:0.438469
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[68] validation_0-logloss:0.438342
[69] validation_0-logloss:0.438323
[70] validation_0-logloss:0.438299
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[77] validation_0-logloss:0.438192
[78] validation_0-logloss:0.438184
[79] validation_0-logloss:0.43816
[80] validation_0-logloss:0.438153
[81] validation_0-logloss:0.438142
[82] validation_0-logloss:0.438133
[83] validation_0-logloss:0.438043
[84] validation_0-logloss:0.438027
```

```
[85] validation_0-logloss:0.438019
[86] validation_0-logloss:0.438015
[87] validation_0-logloss:0.437997
[88] validation_0-logloss:0.437982
[89] validation_0-logloss:0.437969
[90] validation_0-logloss:0.437962
[91] validation_0-logloss:0.437952
[92] validation_0-logloss:0.437944
[93] validation_0-logloss:0.437934
[94] validation_0-logloss:0.437928
[95] validation_0-logloss:0.437921
[96] validation_0-logloss:0.437914
[97] validation_0-logloss:0.437868
[98] validation_0-logloss:0.437871
[99] validation_0-logloss:0.437799
```

Out[297]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, 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='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)
```

In [298]:

```python
y_pred = xgb_clf.predict(x_test)
predictions = [round(value) for value in y_pred]
```

In [299]:

```python
predictions
```

Out[299]:

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In [301]:

```
print(classification_report(y_test,
                            predictions))
```

```
             precision    recall  f1-score   support

      False       0.83      1.00      0.91    248673
       True       0.68      0.00      0.00     51328

avg / total       0.80      0.83      0.75    300001
```

Other evaluation metrics: Accuracy score, Confusion Matrix, ROC/AUC score

In [305]:

```
from sklearn import metrics

print(metrics.accuracy_score(y_test, predictions))
print(metrics.confusion_matrix(y_test, predictions))
print(metrics.roc_auc_score(y_test, predictions))
```

```
0.829060569798
[[248633     40]
 [ 51242     86]]
0.500757322471
```

Saving the XGBoost model

In [319]:

```
import pickle
filename = 'xgb_mod.sav'
filename2 = 'logistic.sav'
pickle.dump(xgb_clf,open(filename, 'wb' ))
pickle.dump(lr_classify, open(filename2, 'wb'))
```