final_test

October 23, 2018

```
In [1]: import os
        import lightgbm as lgb
        import json
        import numpy as np
        import pandas as pd
        import warnings
        from pandas.io.json import json_normalize
        import seaborn as sns
        import matplotlib.pyplot as plt
        import lightgbm
        from sklearn.model_selection import train_test_split
        from sklearn.preprocessing import LabelEncoder
        from sklearn import preprocessing
        from sklearn import metrics
        from datetime import datetime
        from math import sin, cos, sqrt, atan2, radians
        from sklearn import ensemble, metrics
        from sklearn.model_selection import cross_val_score, cross_val_predict
        from sklearn.model_selection import GridSearchCV, KFold, GroupKFold
        from sklearn.metrics import mean_squared_error, classification_report, roc_auc_score, f1
```

```
/anaconda3/lib/python3.6/site-packages/lightgbm/__init__.py:46: UserWarning: Starting from versi
This means that in case of installing LightGBM from PyPI via the ``pip install lightgbm`` comman
Instead of that, you need to install the OpenMP library, which is required for running LightGBM
You can install the OpenMP library by the following command: ``brew install libomp``.
  "You can install the OpenMP library by the following command: ``brew install libomp``.", UserW
```

```
In [2]: def load_df(csv_path='train.csv', nrows=None):
            json_columns = ['device', 'geoNetwork', 'totals', 'trafficSource']

            df = pd.read_csv(csv_path,
                             converters={column: json.loads for column in json_columns},
                             dtype={'fullVisitorId': 'str'}, # Important!!
                             nrows=nrows)

            for column in json_columns:
                column_as_df = json_normalize(df[column])
```

```
            column_as_df.columns = [f"{column}.{subcolumn}" for subcolumn in column_as_df.co
            df = df.drop(column, axis=1).merge(column_as_df, right_index=True, left_index=Tr
        return df
```

In [3]:
```
# Load both train and test data..
train = load_df(nrows = 100000)
test = load_df('test.csv')
```

In [4]:
```
print(train.shape, test.shape)
```

```
(100000, 55) (804684, 53)
```

Task 1: Data Cleaning Following are some of the tasks done as part of data cleaning: (1) The JSON fields are parsed to extract the relevant fields from the entries and create new columns in the dataset for each such entry. (1) Find which fields are missing from test dataset but present in train dataset. Remove all such fields except the target totals.transactionRevenue which will not be absent in test dataset (2) In the data there are fields which are not filled(NULL). It is important to immoute thhese fields so that data is more clean. (3) Remove columns which have a single unique value. These columns are of no use as their value is constant throughout the data, thus can be dropped.

In [5]:
```
# Find which fields are missing from test dataset but present in train dataset.
# Remove all such fields except the target totals.transactionRevenue which will not
# be absent in test dataset
set(train.columns).difference(set(test.columns))
```

Out[5]:
```
{'totals.transactionRevenue', 'trafficSource.campaignCode'}
```

In [6]:
```
train = train.drop(['trafficSource.campaignCode'], axis = 1)
```

In [7]:
```
# Doing some analysis on the data to figure out what can be cleaned
cdf = pd.concat([train.count(), train.nunique(), train.isna().sum()], axis = 1)
cdf = cdf.reset_index()
cdf.columns = ["Column_Name", "Total_Records", "Unique_Values", "Null_Values"]
cdf.sort_values('Unique_Values')[0:20]
```

Out[7]:

	Column_Name	Total_Records \
15	device.mobileDeviceBranding	100000
28	geoNetwork.latitude	100000
35	totals.bounces	48916
37	totals.newVisits	77263
25	geoNetwork.cityId	100000
40	totals.visits	100000
23	device.screenResolution	100000
22	device.screenColors	100000
21	device.operatingSystemVersion	100000
19	device.mobileInputSelector	100000
18	device.mobileDeviceModel	100000

```
17             device.mobileDeviceMarketingName         100000
16                      device.mobileDeviceInfo         100000
29                          geoNetwork.longitude         100000
32                    geoNetwork.networkLocation         100000
12                           device.flashVersion         100000
10                         device.browserVersion         100000
9                             device.browserSize         100000
43  trafficSource.adwordsClickInfo.criteriaParameters    100000
45            trafficSource.adwordsClickInfo.isVideoAd     2574

    Unique_Values  Null_Values
15              1            0
28              1            0
35              1        51084
37              1        22737
25              1            0
40              1            0
23              1            0
22              1            0
21              1            0
19              1            0
18              1            0
17              1            0
16              1            0
29              1            0
32              1            0
12              1            0
10              1            0
9               1            0
43              1            0
45              1        97426
```

In [8]:
```
# Carry out the same thing for the test data as well to make sure the data is actually c
cdf = pd.concat([test.count(), test.nunique(), test.isna().sum()], axis = 1)
cdf = cdf.reset_index()
cdf.columns = ["Column_Name", "Total_Records", "Unique_Values", "Null_Values"]
cdf.sort_values('Unique_Values')[0:20]
```

Out[8]:
```
                           Column_Name  Total_Records  \
14                     device.language         804684
32           geoNetwork.networkLocation         804684
25                   geoNetwork.cityId         804684
35                      totals.bounces         420948
23             device.screenResolution         804684
22                 device.screenColors         804684
21        device.operatingSystemVersion         804684
37                    totals.newVisits         604370
19           device.mobileInputSelector         804684
```

```
18                        device.mobileDeviceModel         804684
17                device.mobileDeviceMarketingName         804684
16                         device.mobileDeviceInfo         804684
15                     device.mobileDeviceBranding         804684
29                            geoNetwork.longitude         804684
28                             geoNetwork.latitude         804684
12                             device.flashVersion         804684
10                           device.browserVersion         804684
9                               device.browserSize         804684
39                                    totals.visits         804684
42  trafficSource.adwordsClickInfo.criteriaParameters         804684

    Unique_Values  Null_Values
14              1            0
32              1            0
25              1            0
35              1       383736
23              1            0
22              1            0
21              1            0
37              1       200314
19              1            0
18              1            0
17              1            0
16              1            0
15              1            0
29              1            0
28              1            0
12              1            0
10              1            0
9               1            0
39              1            0
42              1            0
```

In [9]:
```
def impute_data_fields(train,test):
    # Here we. impute part of the. data, some of the imputations will be done by the lab
    for df in [train, test]:
        if(df is train):
            df['totals.transactionRevenue'] = df['totals.transactionRevenue'].fillna(0)

        df["totals.bounces"] = df["totals.bounces"].fillna(0)
        df["totals.pageviews"] = df["totals.pageviews"].fillna(0)
        df["totals.hits"] = df["totals.hits"].fillna(0)
        df["totals.newVisits"] = df["totals.newVisits"].fillna(0)
```

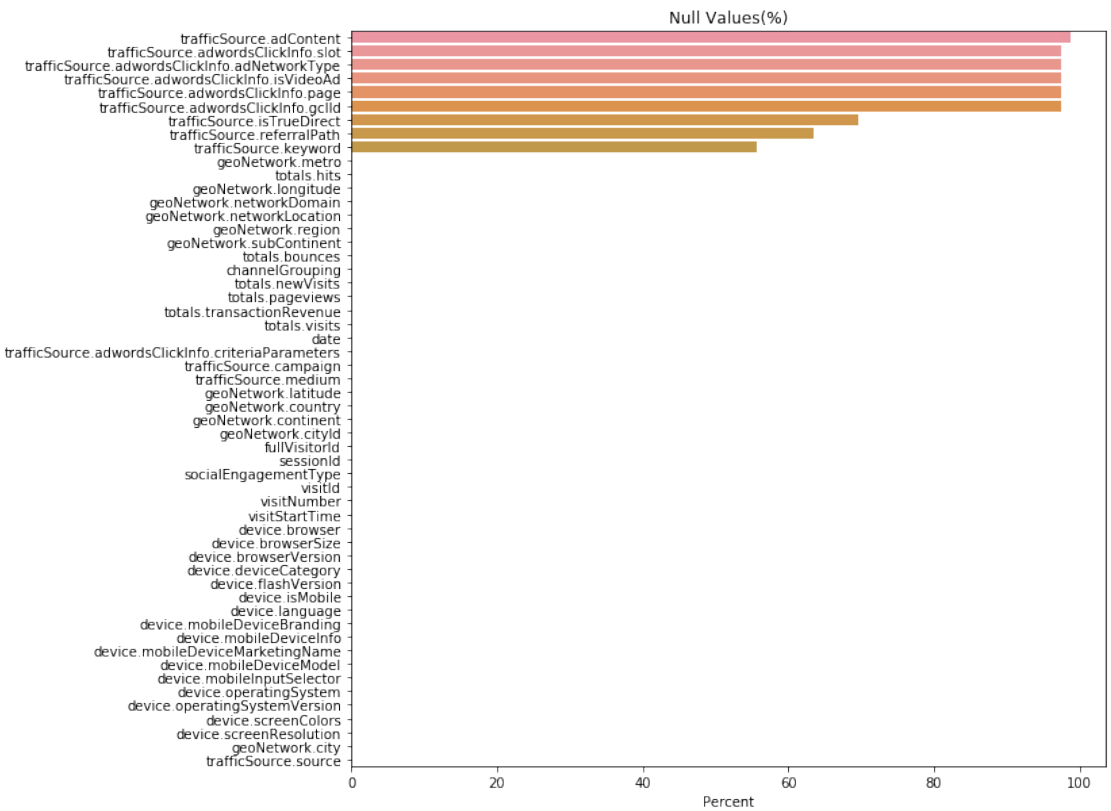
In [10]:
```
impute_data_fields(train,test)
```

In [11]:
```
def get_null_percent(data):
    rows = []
```

```
        for x in data.columns:
            percent = 100-(data[x].count()/data[x].shape[0] * 100)
            rows.append([x,percent])
        output = pd.DataFrame(rows,columns=('Column Name','Null Percent'))
        output = output.sort_values(['Null Percent'], ascending=False)
        return output
```

In [12]:
```
missing_df = get_null_percent(train)
missing_df.shape
plt.figure(figsize = [10,10])
sns.barplot(y = missing_df['Column Name'].values , x=missing_df['Null Percent'].values)
plt.title('Null Values(%)')
plt.xlabel("Percent")
```

Out[12]: Text(0.5,0,'Percent')



In [13]:
```
# Drop all constant columns
def drop_constant_cols(df):
    cols_with_one_value = [c for c in df.columns if df[c].nunique(dropna=False) == 1]
    cols_to_drop = cols_with_one_value
    cols_to_drop.sort()
    df = df.drop(cols_to_drop, axis = 1)
    return df
```

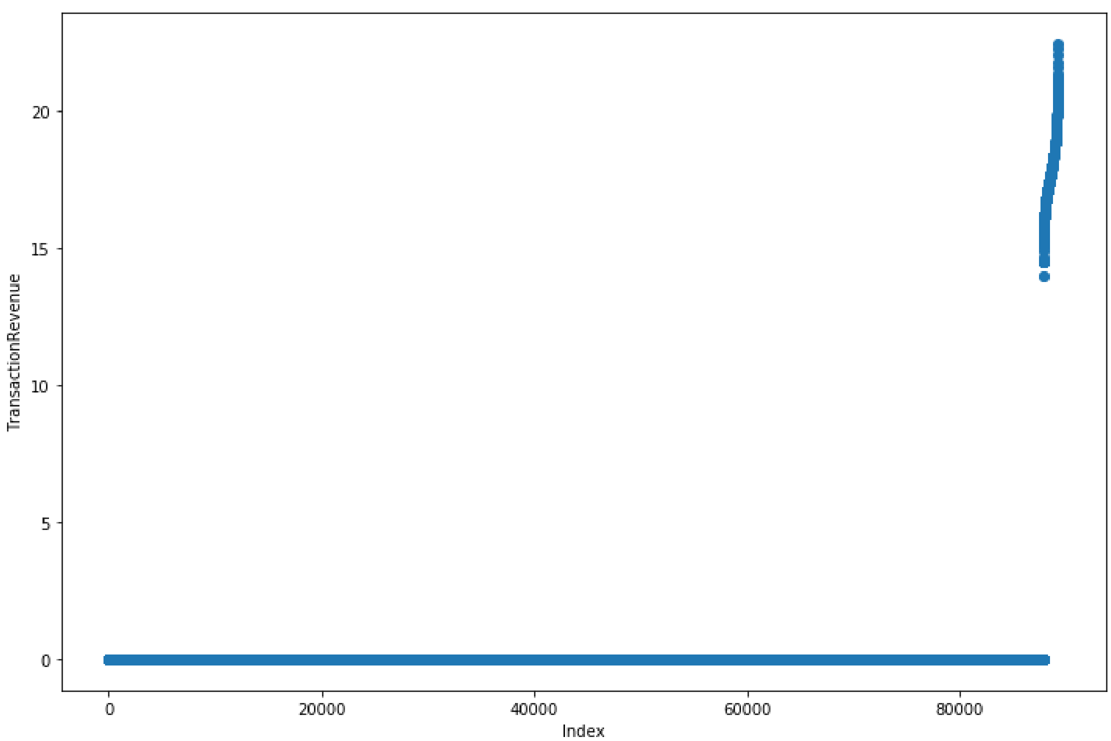
```
In [14]: train = drop_constant_cols(train)
         test = drop_constant_cols(test)
```

```
In [15]: print(train.shape, test.shape)
```

```
(100000, 35) (804684, 34)
```

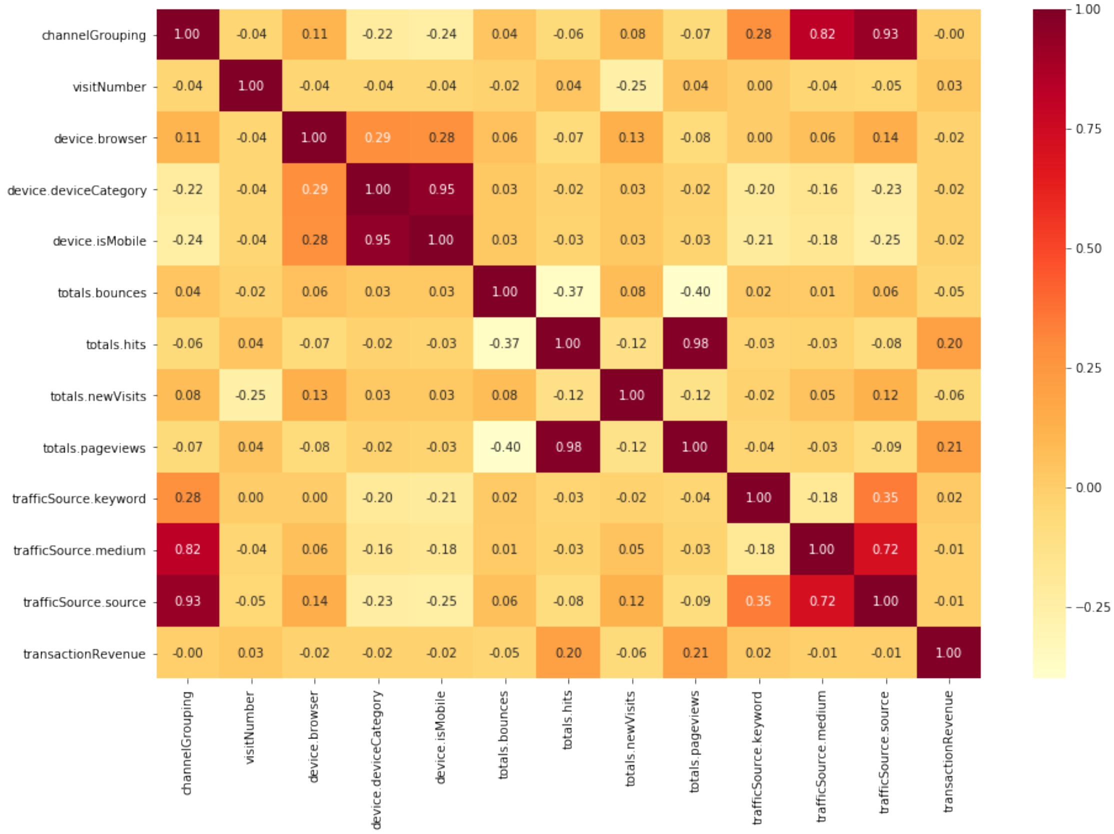
```
In [16]: # Figuring out the 80/20 rule from the data and see if it can be verified from the data
         # Convert the output/target value to float
         train['totals.transactionRevenue'] = train['totals.transactionRevenue'].fillna(0).astyp
```

```
In [17]: # Plot the relation of transaction revenue with user id to confirm the. 80/20 rule in
         # businesses.  We see that indeed most of the revenue comes from a small fraction of th
         # since the plot is densely populated on one end of the axis.
         temp_df = train[["fullVisitorId","totals.transactionRevenue"]].copy()
         target = np.log1p(temp_df.groupby("fullVisitorId")["totals.transactionRevenue"].sum())
         target.describe()

         plt.figure(figsize=(12,8))
         plt.scatter(range(target.shape[0]), np.sort(target.values))
         plt.xlabel('Index', fontsize=10)
         plt.ylabel('TransactionRevenue', fontsize=10)
         plt.show()
```



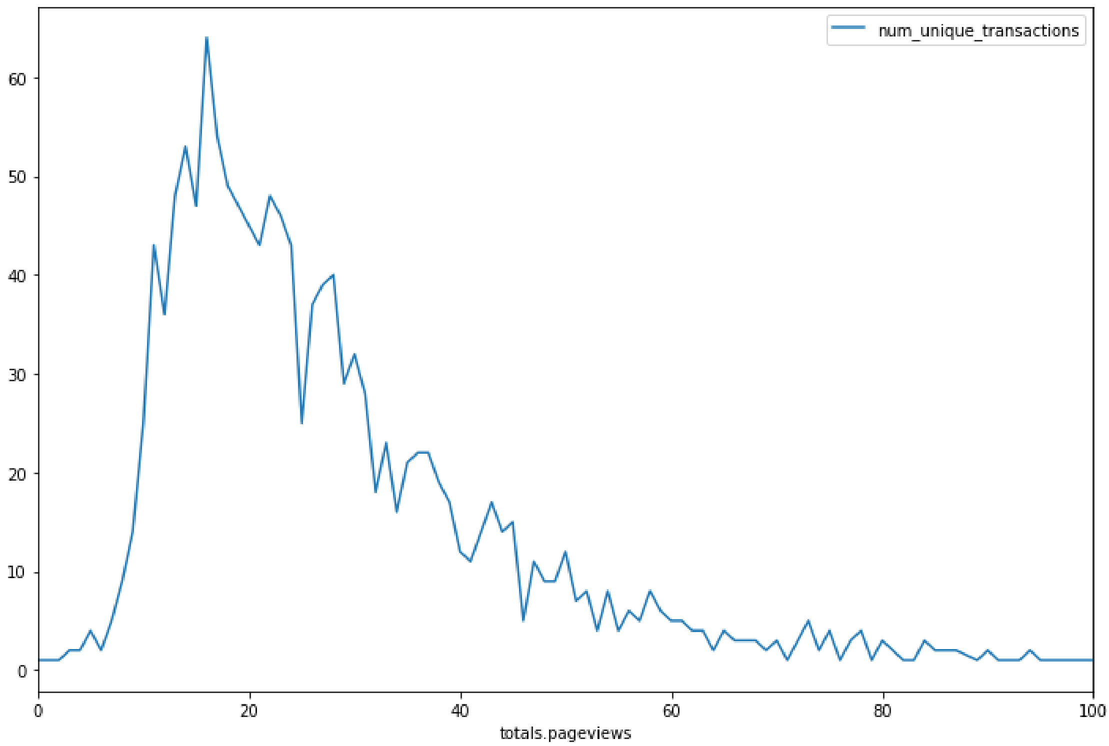
Task 2: Some Interesting Correlations/Plots Some Plots which can help in building better ubderstanding with the data and validating our proof of concept (1) HeatMap - We will plot a heatmap showing the positive/negative correlations in the data variables/features. (2) Plot (1) - We will plot some temporal relation in the data and see if they are consistent with our understandin. It is observed that the transaction revenue is high for a date on which number of visits were high. The plot shows symmetry in the data as well. (3) Plot (2) - We see that count plot shows decreasing nature i.e. we have a very high total count for less number of hits and page views per visitor transaction and the overall count decreases when the number of hits per visitor transaction increases.

```
In [18]: temp_df = train.copy()
         #df['totals.transactionRevenue'] = df['totals.transactionRevenue'].apply(lambda x : 0.0
         #Labeln encode the categorical features before sending to the model for prediction
         all_feat = temp_df.columns

         totals_feat = ['totals.bounces','totals.hits','totals.newVisits', 'totals.pageviews']
         for col in totals_feat:
             temp_df[col] = temp_df[col].astype(np.float)

         temp_df['transactionRevenue'] = temp_df['totals.transactionRevenue'].astype(np.float)

         unused_feat = ['date', 'fullVisitorId', 'sessionId',
                        'totals.transactionRevenue', 'visitId', 'visitStartTime']

         temp_df = temp_df.drop(unused_feat, axis = 1)
         #Removing irrelevant features from the set
         traffic_feat_to_keep = ['trafficSource.keyword', 'trafficSource.medium', 'trafficSource
         geo_feat_to_keep = ['geoNetwork.city', 'geoNetwork.continent', 'geoNetwork.country', \
                             'geoNetwork.metro', 'geoNetwork.networkDomain', 'geoNetwork.region'

         unused_traffic_feat = [c for c in train.columns if c.startswith('traffic') and c not in
         unused_geo_feat = [c for c in train.columns if c.startswith('geoNetwork') and c not in

         irrelevant_feat = unused_traffic_feat + unused_geo_feat + ['device.operatingSystem']

         categorical_feat = [ col for col in temp_df.columns
                              if (col not in unused_feat) & (col not in irrelevant_feat) & (t

         for column in categorical_feat:
             lbe = preprocessing.LabelEncoder()
             lbe.fit(list(temp_df[column].values.astype('str')))
             temp_df[column] = lbe.transform(list(temp_df[column].values.astype('str')))
         corr = temp_df.corr()
         plt.figure(figsize=(15, 10))
         sns.heatmap(corr,annot=True, fmt="0.2f", cmap='YlOrRd')

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x1b5dcd0278>
```

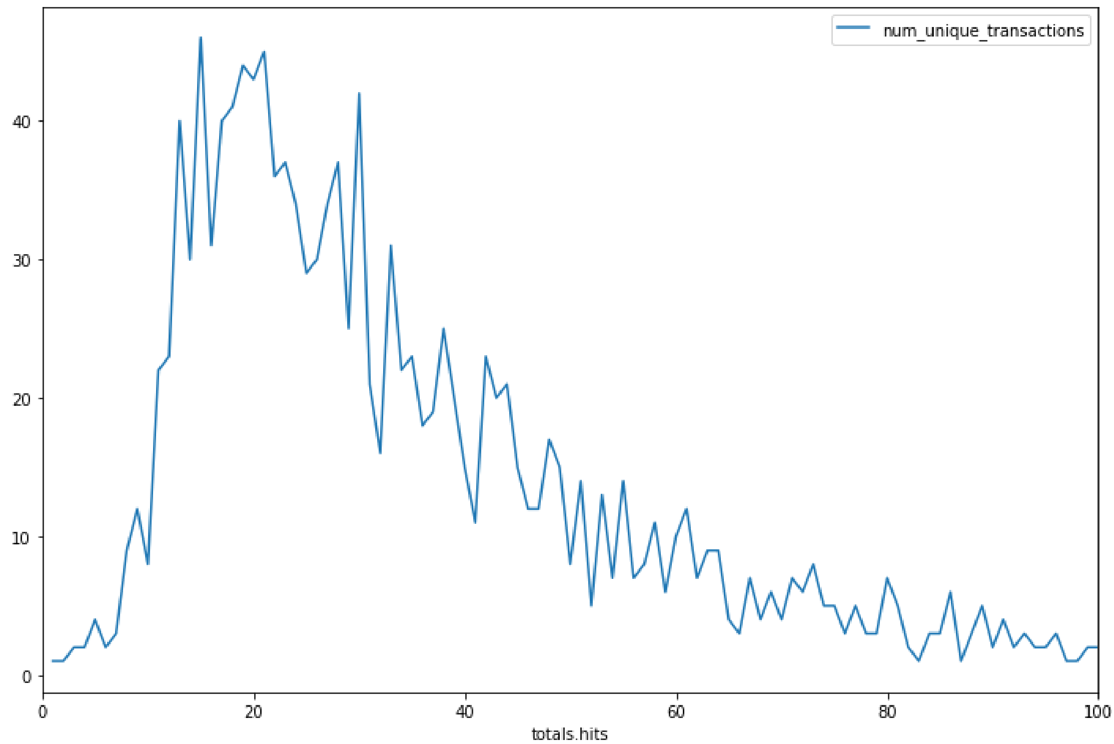


In [19]:
```
totals_feat = ['totals.bounces','totals.hits','totals.newVisits', 'totals.pageviews']
df = pd.DataFrame()
for col in totals_feat:
    df[col] = train[col].astype(np.float)

df['transactionRevenue'] = train['totals.transactionRevenue'].astype(np.float)
temp = df.groupby('totals.pageviews')['transactionRevenue'].unique()
df_new = pd.DataFrame(temp)
df_new['num_unique_transactions'] = [len(temp[c]) for c in temp.index]
del df_new['transactionRevenue']
df_new = df_new.reset_index()
df_new.plot('totals.pageviews', 'num_unique_transactions',xlim = (0,100), figsize=(12,8
```

Out[19]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1b5dd31898>
```




```
In [20]: temp = df.groupby('totals.hits')['transactionRevenue'].unique()
         df_new = pd.DataFrame(temp)
         df_new['num_unique_transactions'] = [len(temp[c]) for c in temp.index]
         del df_new['transactionRevenue']
         df_new = df_new.reset_index()
         df_new.plot('totals.hits', 'num_unique_transactions', xlim = (0,100), figsize=(12,8))

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x1b5da3dfd0>
```



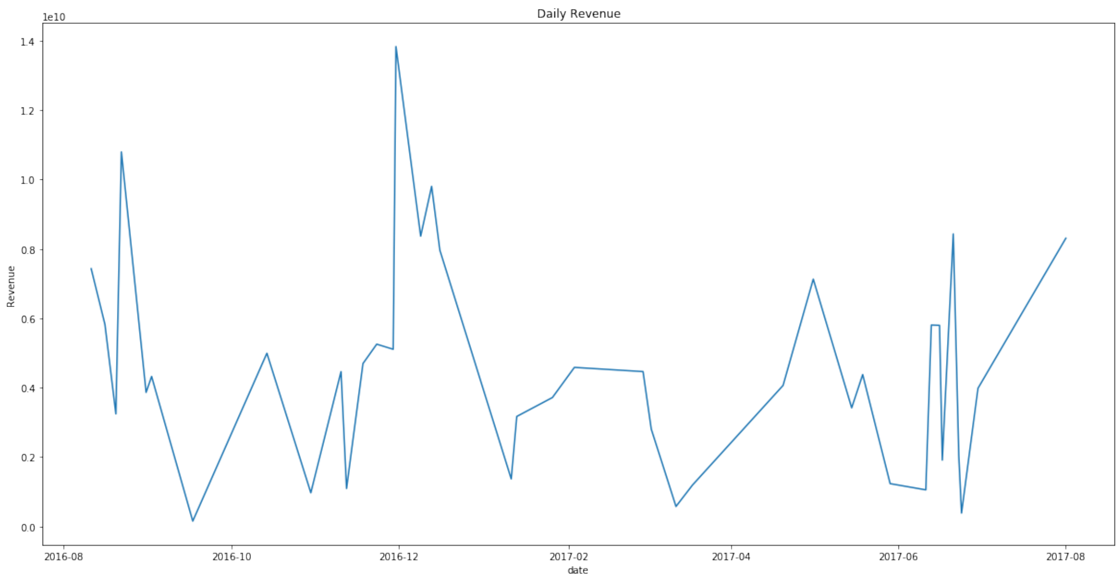

```
In [21]: def plot_data(data, col, title='',size=(7,7),topx = 10, showplot = True):
             df = pd.DataFrame()
             # Normalize the count so that it can be analyzed easily.
             plotdata0 = data.groupby(col)['totals.transactionRevenue'].size()/len(data)
             df['Normalized_Count'] = plotdata0
             plotdata1 = data.groupby(col)['totals.transactionRevenue'].count()
             df['Non_Zero_Revenue_Count'] = plotdata1
             plotdata2 = data.groupby(col)['totals.transactionRevenue'].mean()
             df['Mean_Revenue'] = plotdata2
             df = df.sort_values('Normalized_Count', ascending=False)[0:topx]
             if(showplot):
                 f, axes = plt.subplots(3, 1, figsize=size, sharex=True, squeeze=False)
                 axes[0][0].set_title(title + " : Total Count Normalized")
                 axes[0][0].set_ylabel('Normalized Count')
                 axes[1][0].set_title(title + " : Non Zero Revenue Count")
                 axes[1][0].set_ylabel('Non Zero Revenue Count')
                 axes[2][0].set_title(title + " : Mean Revenue")
                 axes[2][0].set_ylabel('Mean Revenue')
                 sns.barplot(x = df.index, y=df.Normalized_Count, ax = axes[0][0])
                 sns.barplot(x = df.index, y=df.Non_Zero_Revenue_Count, ax=axes[1][0])
                 sns.barplot(x = df.index, y=df.Mean_Revenue, ax=axes[2][0])
                 plt.show()
             else:
```

```
        return df
```

In [22]:
```
# Now we will see some temporal relation in the data and see if they are consistent
# with our understandin. It is observed that the transaction revenue is high for a date
# number of visits were high. The plot shows symmetry in the data as well.
```

In [23]:
```
#Lets do some more time/date based analysis
train["formated_date"] = pd.to_datetime(train["date"],format="%Y%m%d")
revenue_date_df = train[["totals.transactionRevenue" , "formated_date"]].dropna()
revenue_date_df["totals.transactionRevenue"] = revenue_date_df["totals.transactionReven
daily_revenue_df = revenue_date_df.groupby(by=["formated_date"],axis = 0 ).sum()
fig, axes = plt.subplots(figsize=(20,10))
axes.set_title("Daily Revenue")
axes.set_ylabel("Revenue")
axes.set_xlabel("date")
axes.plot(daily_revenue_df["totals.transactionRevenue"])
```

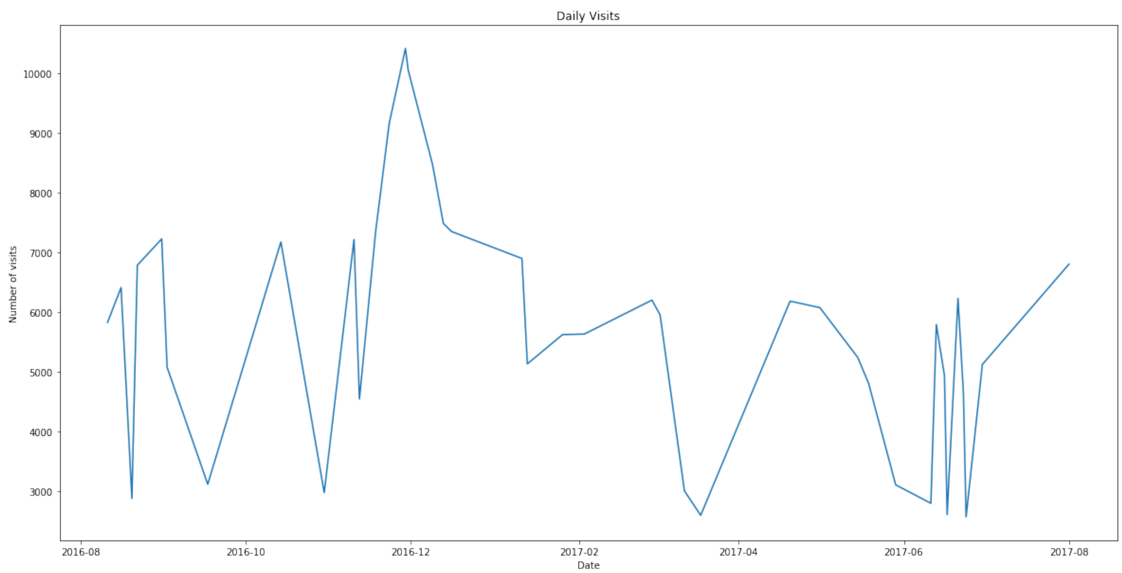
Out[23]:
```
[<matplotlib.lines.Line2D at 0x1b5d9ecda0>]
```



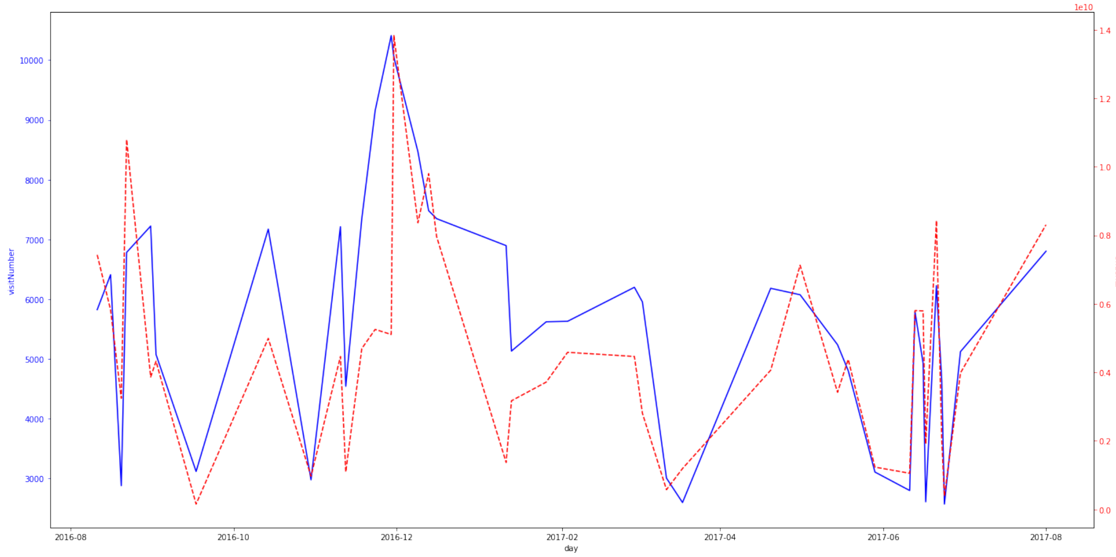
In [24]:
```
visit_dt_df = train[["formated_date","visitNumber"]]
visit_dt_df["visitNumber"] = visit_dt_df.visitNumber.astype(np.int64)

daily_visit_df = visit_dt_df.groupby(by=["formated_date"], axis = 0).sum()

fig, axes = plt.subplots(1,1,figsize=(20,10))
axes.set_ylabel("Number of visits")
axes.set_xlabel("Date")
axes.set_title("Daily Visits")
axes.plot(daily_visit_df["visitNumber"])
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: 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: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
```

Out[24]: [<matplotlib.lines.Line2D at 0x1b5ddbb3c8>]

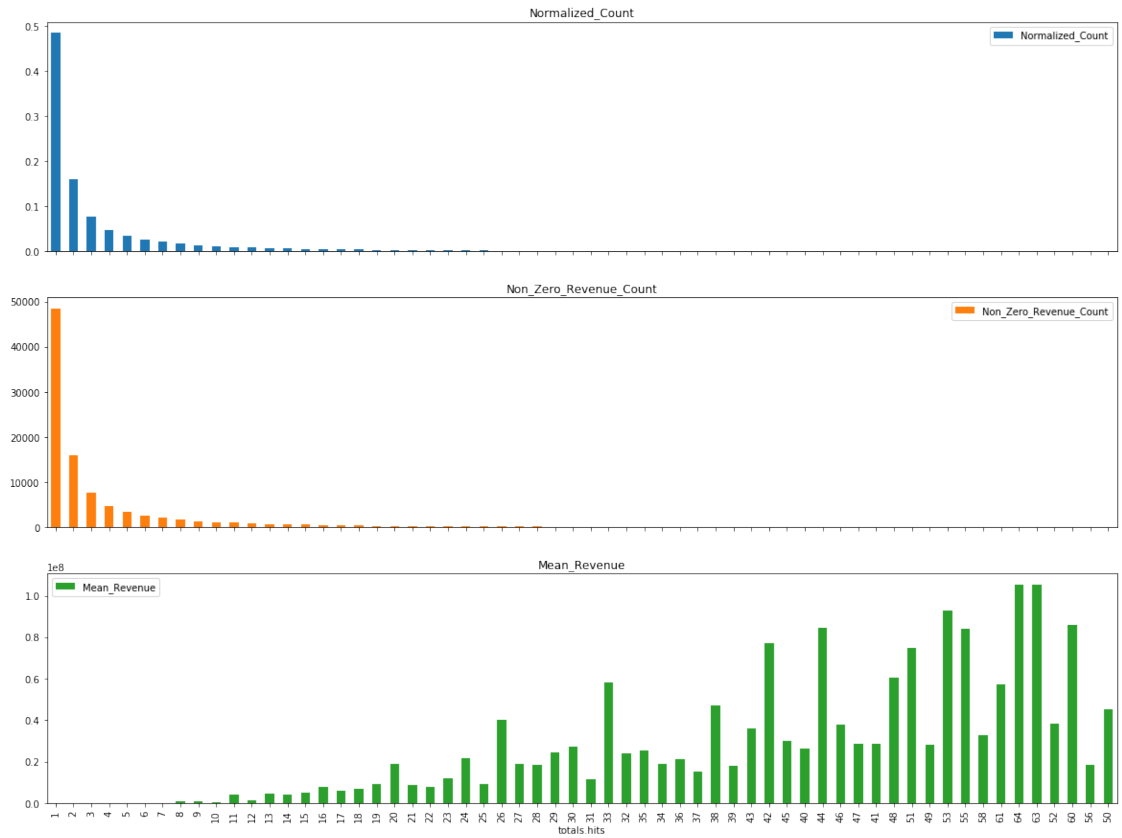


In [25]:
```
total_revenue_daily_df = revenue_date_df.groupby(by=["formated_date"],axis=0).sum()
total_visitNumber_daily_df = train[["formated_date","visitNumber"]].groupby(by=["format
datetime_revenue_visits_df = pd.concat([total_revenue_daily_df,total_visitNumber_daily_

fig, ax1 = plt.subplots(figsize=(20,10))
t = datetime_revenue_visits_df.index
s1 = datetime_revenue_visits_df["visitNumber"]
ax1.plot(t, s1, 'b-')
ax1.set_xlabel('day')
# Make the y-axis label, ticks and tick labels match the line color.
ax1.set_ylabel('visitNumber', color='b')
ax1.tick_params('y', colors='b')

ax2 = ax1.twinx()
s2 = datetime_revenue_visits_df["totals.transactionRevenue"]
ax2.plot(t, s2, 'r--')
ax2.set_ylabel('revenue', color='r')
ax2.tick_params('y', colors='r')
fig.tight_layout()
```




```
In [26]: # Plot (2):
         #We see that count plot shows decreasing nature i.e. we have a very high total count fo
         #and page views per visitor transaction and the overall count decreases when the number
         #per visitor transaction increases.
         df = plot_data(data=train, col='totals.hits', title='Total - PageViews', size=[15,15],
         df.plot.bar(subplots=True, figsize = (20,15))
```

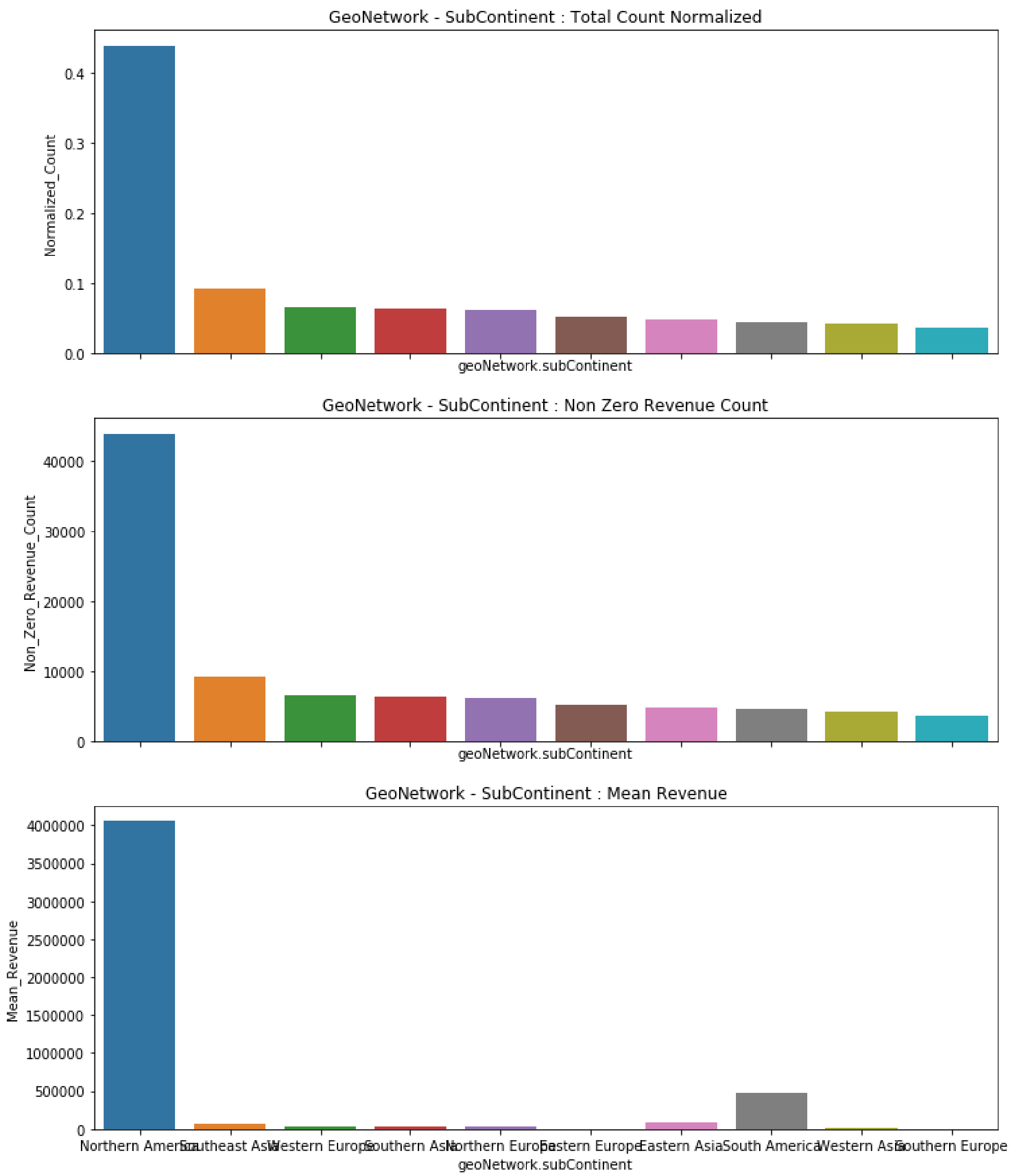
```
Out[26]: array([<matplotlib.axes._subplots.AxesSubplot object at 0x1b5d98a748>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x1b5d8d3e48>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x1b5d8af358>],
               dtype=object)
```



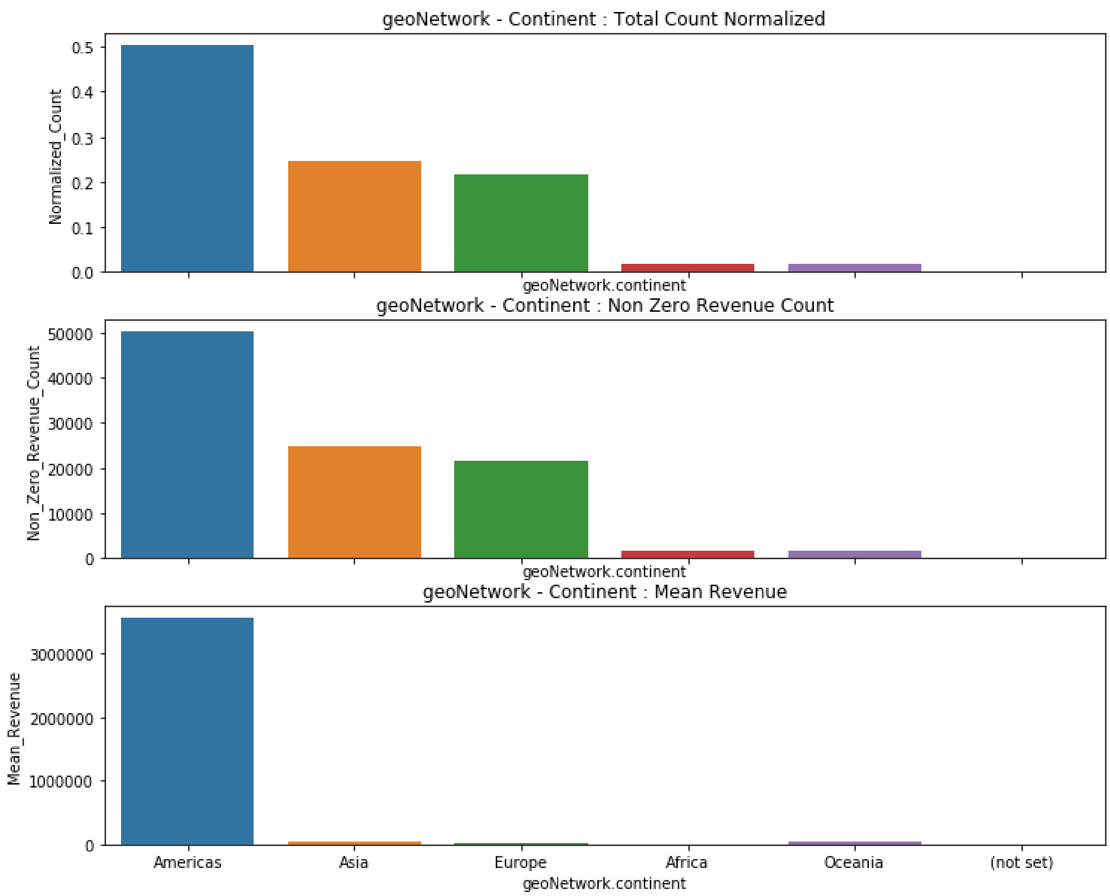

```
In [27]: df = plot_data(data=train, col='totals.pageviews', title='Total - PageViews', size=[15,
         df.plot.bar(subplots=True, figsize = (20,15))

Out[27]: array([<matplotlib.axes._subplots.AxesSubplot object at 0x1b5d7dc080>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x1b5d504d68>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x1b5d4d9470>],
               dtype=object)
```

Task 3: Clustering data on Geography
Plot 1 is a set of three plots each depicting the number of visits done by users of each city to the site these include visits that resulted into transactions as well those which didn't. I have plotted the normalized value as the range in order to prevent scaling issues. The second plot in the subplot tells the count of non zero transactions made by users of a city. The third subplot shows the mean revenue generated by each city. Similar plots have been plotted for continent, city, subcontinent etc.

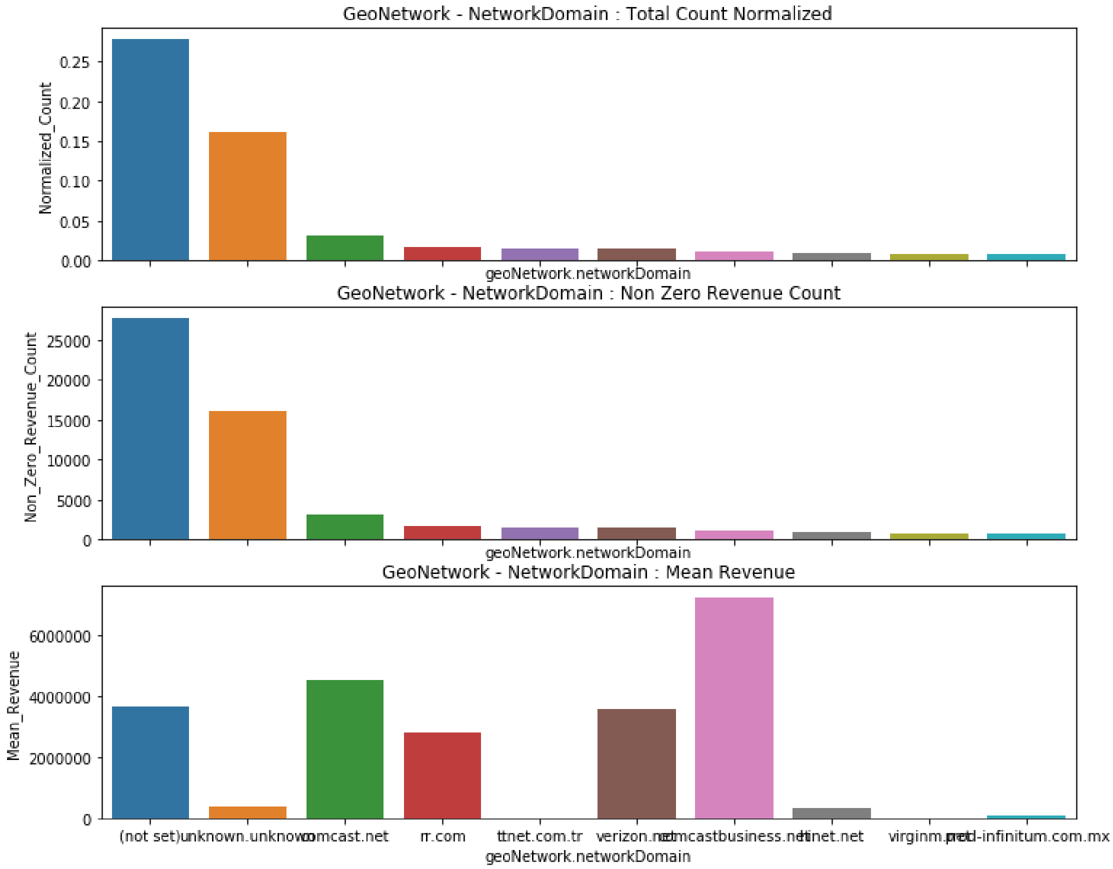
```
In [28]: plot_data(data=train, col='geoNetwork.subContinent', title='GeoNetwork - SubContinent',
```



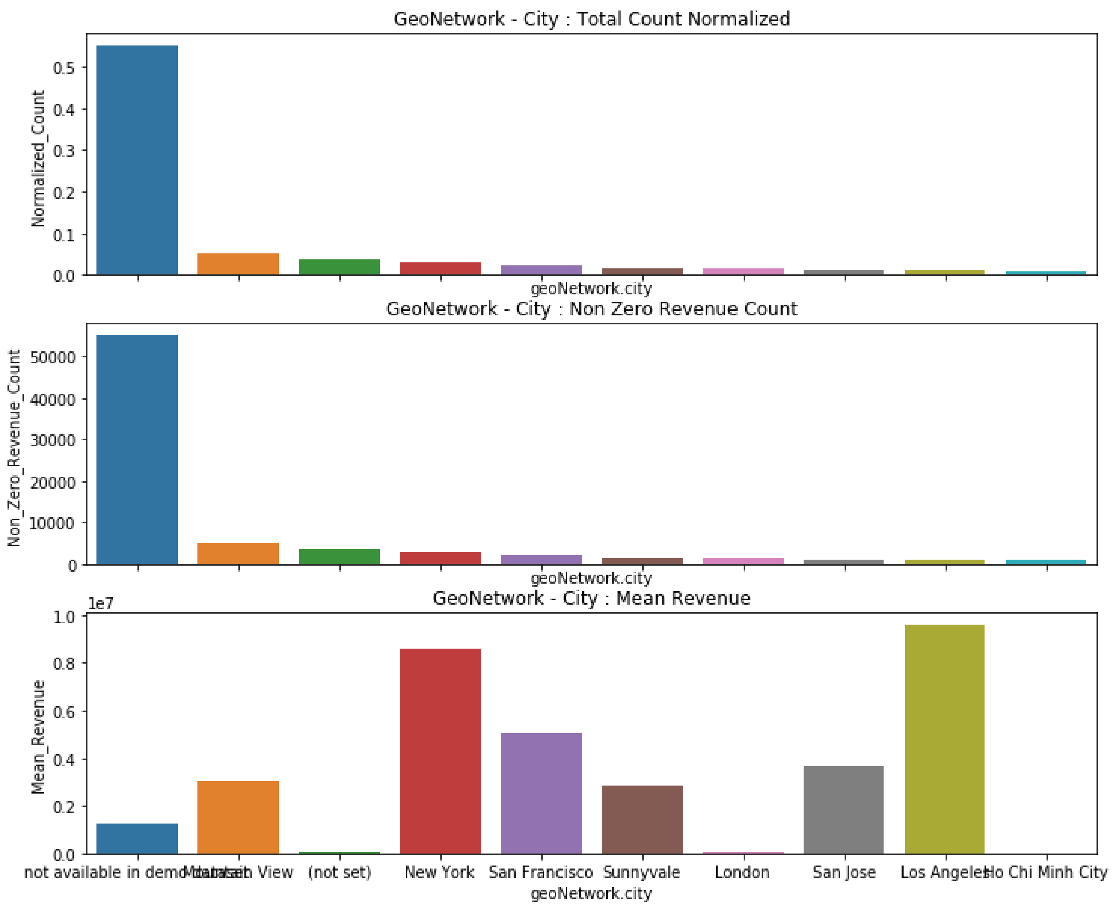

```
In [29]: plot_data(data=train, col='geoNetwork.continent', title='geoNetwork - Continent', size=
```




```
In [30]: plot_data(data=train, col='geoNetwork.networkDomain', title='GeoNetwork - NetworkDomain
```




```
In [31]: plot_data(data=train, col='geoNetwork.city', title='GeoNetwork - City', size=[12,10])
```



Task 4: Buying Score/Probability

In [32]:
```
# Lets group the data based on user id in order to give it a score. For this we will fi
# made to the store and total number of transactions he did. based on these two data we
# score for each user id
df_new = train[['fullVisitorId','visitNumber','totals.transactionRevenue']].copy()
df_new['totals.transactionRevenue'] = df_new['totals.transactionRevenue'].astype(bool)
agg_dict = {}
agg_dict['visitNumber'] = "max"
agg_dict['totals.transactionRevenue'] = "sum"
df_new = df_new.groupby('fullVisitorId').agg(agg_dict).reset_index()
df_new[df_new['totals.transactionRevenue'] > 1].head()
```

Out[32]:

	fullVisitorId	visitNumber	totals.transactionRevenue
4038	0463325773564352787	4	2.0
5272	0608915197735218105	6	2.0
5577	0642830728760694475	9	2.0
9816	1111470101899387454	4	2.0
10162	1152867987950849273	2	2.0

```
In [33]: df_new['buy_probability'] = df_new['totals.transactionRevenue']/df_new['visitNumber']
         top_clients = df_new.sort_values('buy_probability', ascending= False)['fullVisitorId'][
         print("Client Id's of top 10 users who are most likely to buy from GStore are : \n" , t
```

```
Client Id's of top 10 users who are most likely to buy from GStore are :
 ['653069947099114599' '2518447979646501002' '9710480501909231921'
 '8186007457246709564' '3614707430894059857' '6275380876231092642'
 '144847938814859371' '5970035247923497864' '1881458907401964229'
 '3112141012835314636']
```

```
In [34]: #session_feat = ['sessionId','visitId','visitStartTime']
         totals_feat = ['totals.bounces','totals.hits','totals.newVisits', 'totals.pageviews']
         target_col = ['totals.transactionRevenue']
         numerical_feat = totals_feat + ['visitNumber']

         for column_iter in numerical_feat:
             train[column_iter] = train[column_iter].astype(np.float)
             test[column_iter] = test[column_iter].astype(np.float)
```

```
In [35]: # This feature breaks down the date into multiple fields like dya, year , month and oth
         def add_date_feature(df):
             df['formated_date'] = pd.to_datetime(df['date'].apply(lambda x: str(x)[:4] + '-' +
             df['month'] = df['formated_date'].dt.month
             df['day'] = df['formated_date'].dt.day
             df['year'] = df['formated_date'].dt.year
             df['weekday'] = df['formated_date'].dt.weekday
             df['weekofyear'] = df['formated_date'].dt.weekofyear
             #Do the same processing for test data as well to keep it consistent with the train
             df = df.drop(['formated_date'], axis=1)
             return df

         # This feature groups the data on fullVisitorId to figure out how many transactions eac
         def add_buycount_feature(df):
             buycount = df.groupby('fullVisitorId')['visitId'].count().reset_index()
             buycount.columns = ['fullVisitorId','buy_count']
             df = pd.merge(train, buycount, on=['fullVisitorId'], how='left')
             df['buy_count'].fillna(0, inplace=True)
             return df

         # This feature will
         def add_hit_rate_feature(df):
             df['hit_rate'] = df['totals.hits'] / df['totals.pageviews']
             return df
```

```
In [36]: def add_features(df):
             # Add date extracted date columns
             df = add_date_feature(df)
             # Add buycount feature ==> Cumulative visits on the store for each user/sessionId
```

```
    #df = add_buycount_feature(df)
    # Add hit_rate_feature
    df = add_hit_rate_feature(df)
    # Some more features based on aggregation of columns
    df['month_unique_user_count'] = df.groupby('month')['fullVisitorId'].transform('nun
    df['day_unique_user_count'] = df.groupby('day')['fullVisitorId'].transform('nunique
    df['weekday_unique_user_count'] = df.groupby('weekday')['fullVisitorId'].transform(
    df['weekofyear_unique_user_count'] = df.groupby('weekofyear')['fullVisitorId'].tran
    df['mean_hits_per_day'] = df.groupby(['day'])['totals.hits'].transform('mean')
    df['sum_hits_per_day'] = df.groupby(['day'])['totals.hits'].transform('sum')
    df['user_pageviews_sum'] = df.groupby('fullVisitorId')['totals.pageviews'].transfor
    df['user_hits_sum'] = df.groupby('fullVisitorId')['totals.hits'].transform('sum')
    df['user_pageviews_count'] = df.groupby('fullVisitorId')['totals.pageviews'].transf
    df['user_hits_count'] = df.groupby('fullVisitorId')['totals.hits'].transform('count


    return df
```

In [37]:
```
# Add some extra features to the data to improve the predictions
train = add_features(train)
test = add_features(test)
```

Task 5: Adding Extrernal Dataset I picked up an external dataset from Kaggle itself from the following link https://www.kaggle.com/satian/exported-google-analytics-data. There are couple of important fields in this including avg session time, goal conversion rate etc.

In [38]:
```
#Add some external dataset to improve the model performance.
train_ext = pd.read_csv('Train_external_data.csv',skiprows=6, dtype={"Client Id":'str'}
test_ext = pd.read_csv('Test_external_data.csv',skiprows=6, dtype={"Client Id":'str'})
```

In [39]:
```
train_ext["visitId"] = train_ext["Client Id"].apply(lambda x: x.split('.', 1)[1]).astyp
test_ext["visitId"] = test_ext["Client Id"].apply(lambda x: x.split('.', 1)[1]).astype(
```

In [40]:
```
# Since Visit id is common among the ths given data set and external dataset,we will me
# the external set on visitID but before that we need to convert the visitId to numeric
# object
for df in [train, test, train_ext, test_ext]:
    df["visitId"] = df["visitId"].astype(int)

train = train.merge(train_ext, how="left", on="visitId")
test = test.merge(test_ext, how="left", on="visitId")
```

In [41]:
```
# Drop Client Id
for df in [train, test]:
    df.drop("Client Id",axis = 1, inplace=True)
```

In [42]:
```
# Remove $ from revenue field and fill empty fields with 0
for df in [train, test]:
    df_new = pd.DataFrame()
```

```
            df_new['Revenue'] = df["Revenue"].fillna('$')
            df_new["Revenue"] = df_new["Revenue"].apply(lambda x: x.replace('$', '').replace(',
            df_new['Revenue'] = pd.to_numeric(df_new['Revenue'],errors="coerce")
            df_new["Revenue"] = df_new["Revenue"].fillna(0.0)
            df['Revenue'] = df_new["Revenue"]
        #  df['is_high_hits'] = np.logical_or(df["totals.hits"]>4,df["totals.pageviews"]>4).a
         # df['views/hits']= df["totals.pageviews"]/df["totals.hits"].dropna(0)
```

In [43]:
```
def impute_ext_data_fields(df):
            df["Sessions"] = df["Sessions"].fillna(0)
            df['Bounce Rate'] = df['Bounce Rate'].fillna(0)
            df["Avg. Session Duration"] = df["Avg. Session Duration"].fillna(0)
            df["Transactions"] = df["Transactions"].fillna(0)
            df["Goal Conversion Rate"] = df["Goal Conversion Rate"].fillna(0)
            return df
```

In [44]:
```
train = impute_ext_data_fields(train)
test = impute_ext_data_fields(test)
```

In [45]:
```
target = train['totals.transactionRevenue']
```

In [46]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100001 entries, 0 to 100000
Data columns (total 57 columns):
channelGrouping                               100001 non-null object
date                                          100001 non-null int64
fullVisitorId                                 100001 non-null object
sessionId                                     100001 non-null object
visitId                                       100001 non-null int64
visitNumber                                   100001 non-null float64
visitStartTime                                100001 non-null int64
device.browser                                100001 non-null object
device.deviceCategory                         100001 non-null object
device.isMobile                               100001 non-null bool
device.operatingSystem                        100001 non-null object
geoNetwork.city                               100001 non-null object
geoNetwork.continent                          100001 non-null object
geoNetwork.country                            100001 non-null object
geoNetwork.metro                              100001 non-null object
geoNetwork.networkDomain                      100001 non-null object
geoNetwork.region                             100001 non-null object
geoNetwork.subContinent                       100001 non-null object
totals.bounces                                100001 non-null float64
totals.hits                                   100001 non-null float64
totals.newVisits                              100001 non-null float64
totals.pageviews                              100001 non-null float64
totals.transactionRevenue                     100001 non-null float64
```

```
trafficSource.adContent                        1325 non-null object
trafficSource.adwordsClickInfo.adNetworkType   2574 non-null object
trafficSource.adwordsClickInfo.gclId           2625 non-null object
trafficSource.adwordsClickInfo.isVideoAd       2574 non-null object
trafficSource.adwordsClickInfo.page            2574 non-null object
trafficSource.adwordsClickInfo.slot            2574 non-null object
trafficSource.campaign                         100001 non-null object
trafficSource.isTrueDirect                     30454 non-null object
trafficSource.keyword                          44218 non-null object
trafficSource.medium                           100001 non-null object
trafficSource.referralPath                     36473 non-null object
trafficSource.source                           100001 non-null object
month                                          100001 non-null int64
day                                            100001 non-null int64
year                                           100001 non-null int64
weekday                                        100001 non-null int64
weekofyear                                     100001 non-null int64
hit_rate                                       100001 non-null float64
month_unique_user_count                        100001 non-null int64
day_unique_user_count                          100001 non-null int64
weekday_unique_user_count                      100001 non-null int64
weekofyear_unique_user_count                   100001 non-null int64
mean_hits_per_day                              100001 non-null float64
sum_hits_per_day                               100001 non-null float64
user_pageviews_sum                             100001 non-null float64
user_hits_sum                                  100001 non-null float64
user_pageviews_count                           100001 non-null int64
user_hits_count                                100001 non-null int64
Sessions                                       100001 non-null float64
Avg. Session Duration                          100001 non-null object
Bounce Rate                                    100001 non-null object
Revenue                                        100001 non-null float64
Transactions                                   100001 non-null float64
Goal Conversion Rate                           100001 non-null object
dtypes: bool(1), float64(14), int64(14), object(28)
memory usage: 43.6+ MB
```

```
In [47]: all_feat = train.columns

         unused_feat = ['date', 'fullVisitorId', 'sessionId',
                        'totals.transactionRevenue', 'visitId', 'visitStartTime']

         #Removing irrelevant features from the set
         traffic_feat_to_keep = ['trafficSource.keyword', 'trafficSource.medium', 'trafficSource

         unused_traffic_feat = [c for c in train.columns if c.startswith('traffic') and c not in
         unused_geo_feat = []
```

```
irrelevant_feat = unused_traffic_feat + unused_geo_feat + ['device.operatingSystem']

categorical_feat = [ col for col in train.columns
                     if (col not in unused_feat) & (col not in irrelevant_feat) & (t

print(categorical_feat)
# Take the log of the prediction outout before passing it to the model
target = np.log1p(target)

df_train = train.drop(unused_feat, axis = 1)
# Unused features for test data will not have totals.transactions
unused_feat_test = unused_feat.copy()
unused_feat_test.remove('totals.transactionRevenue')
df_test = test.drop(unused_feat_test, axis = 1)

df_train = df_train.drop(irrelevant_feat, axis = 1)
df_test = df_test.drop(irrelevant_feat, axis = 1)

df_train["Revenue"] = np.log1p(df_train["Revenue"])
df_test["Revenue"] = np.log1p(df_test["Revenue"])

ext_categorical_features =  ['Bounce Rate', 'Goal Conversion Rate', 'Revenue']

categorical_feat += ext_categorical_features
#Labeln encode the categorical features before sending to the model for prediction to c
# as the model might complain if the input is fed as a string
for column in categorical_feat:
    lbe = preprocessing.LabelEncoder()
    lbe.fit(list(df_train[column].values.astype('str')) + list(df_test[column].values.a
    df_train[column] = lbe.transform(list(df_train[column].values.astype('str')))
    df_test[column] = lbe.transform(list(df_test[column].values.astype('str')))
```

```
['channelGrouping', 'device.browser', 'device.deviceCategory', 'geoNetwork.city', 'geoNetwork.co
```

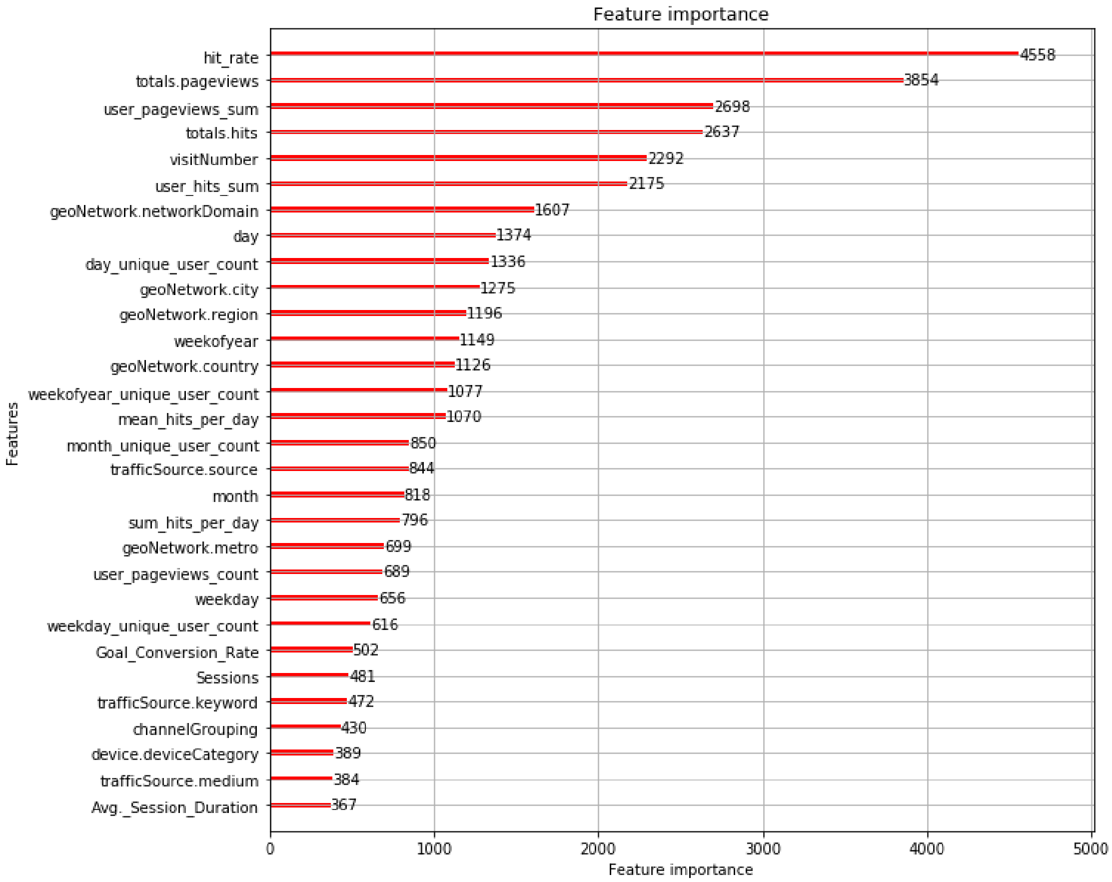
Task 6: Predictive Modeling I have used a KFold LGBM model for prediction. The model works fairly good and provide quite nice RMSE value

```
In [48]: params = {
                 "objective" : "regression",
                 "metric" : "rmse",
                 "max_depth": 8,
                 "min_child_samples": 20,
                 "reg_alpha": 0.2,
                 "reg_lambda": 0.2,
                 "num_leaves" : 257,
                 "learning_rate" : 0.01,
```

```
                "subsample" : 0.9,
                "colsample_bytree" : 0.9,
                "subsample_freq ": 5
            }
    n_fold = 10
    folds = KFold(n_splits=n_fold, shuffle=False, random_state=42)
    # Cleaning and defining parameters for LGBM
    model = lgb.LGBMRegressor(**params, n_estimators = 20000, nthread = 4, n_jobs = -1)
    prediction = np.zeros(df_test.shape[0])

    for fold_n, (train_index, test_index) in enumerate(folds.split(df_train)):
        print('Fold:', fold_n)
        #print(f'Train samples: {len(train_index)}. Valid samples: {len(test_index)}')
        X_train, X_valid = df_train.iloc[train_index], df_train.iloc[test_index]
        y_train, y_valid = target.iloc[train_index], target.iloc[test_index]


        model.fit(X_train, y_train,
                eval_set=[(X_train, y_train), (X_valid, y_valid)], eval_metric='rmse',
                verbose=500, early_stopping_rounds=100)

        y_pred = model.predict(df_test, num_iteration=model.best_iteration_)
        prediction += y_pred
    prediction /= n_fold

    lgb.plot_importance(model, max_num_features=30, color='r',figsize=(10,10));
```

```
Fold: 0
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[163]        training's rmse: 1.54504        valid_1's rmse: 1.44014
Fold: 1
Training until validation scores don't improve for 100 rounds.
[500]        training's rmse: 1.33918        valid_1's rmse: 1.75255
Early stopping, best iteration is:
[576]        training's rmse: 1.32891        valid_1's rmse: 1.75058
Fold: 2
Training until validation scores don't improve for 100 rounds.
[500]        training's rmse: 1.39404        valid_1's rmse: 1.17363
Early stopping, best iteration is:
[624]        training's rmse: 1.37784        valid_1's rmse: 1.17126
Fold: 3
Training until validation scores don't improve for 100 rounds.
[500]        training's rmse: 1.34912        valid_1's rmse: 1.79977
[1000]        training's rmse: 1.2841        valid_1's rmse: 1.78815
[1500]        training's rmse: 1.22485        valid_1's rmse: 1.7795
Early stopping, best iteration is:
[1818]        training's rmse: 1.18601        valid_1's rmse: 1.77765
```

```
Fold: 4
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.34611	valid_1's rmse: 1.70558
Early stopping, best iteration is:
[553]	training's rmse: 1.33894	valid_1's rmse: 1.70523
Fold: 5
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[359]	training's rmse: 1.39789	valid_1's rmse: 1.61475
Fold: 6
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[150]	training's rmse: 1.55783	valid_1's rmse: 1.57743
Fold: 7
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.33786	valid_1's rmse: 1.90234
[1000]	training's rmse: 1.2711	valid_1's rmse: 1.89592
Early stopping, best iteration is:
[901]	training's rmse: 1.28697	valid_1's rmse: 1.89576
Fold: 8
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.30096	valid_1's rmse: 2.05199
Early stopping, best iteration is:
[606]	training's rmse: 1.28347	valid_1's rmse: 2.05115
Fold: 9
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.36581	valid_1's rmse: 1.44486
Early stopping, best iteration is:
[542]	training's rmse: 1.35947	valid_1's rmse: 1.44438
```




```
In [49]: submission = test[['fullVisitorId']].copy()
         submission.loc[:, 'PredictedLogRevenue'] = prediction
         submission["PredictedLogRevenue"] = submission["PredictedLogRevenue"].apply(lambda x :
         submission["PredictedLogRevenue"] = submission["PredictedLogRevenue"].fillna(0.0)
         grouped_test = submission[['fullVisitorId', 'PredictedLogRevenue']].groupby('fullVisito
         grouped_test.to_csv('submission.csv',index=False)
```

Task 7: Permutation Test In this we try to find the relevance/significance of a particular data for prediction. The idea is to permute the values of any given column of the

```
In [62]: import time
         def modelForPermutation():
             pred = np.zeros(len(df_test))
             for fold_n, (train_idx, valid_idx) in enumerate(folds.split(df_train)):
                 print('Fold', fold_n, 'started at', time.ctime())
                 X_train, X_valid = df_train.iloc[train_idx], df_train.iloc[valid_idx]
                 y_train, y_valid = target.iloc[train_idx], target.iloc[valid_idx]

                 model.fit(X_train, y_train,
```

```
                        eval_set=[(X_train, y_train), (X_valid, y_valid)], eval_metric='rmse',
                        verbose=500, early_stopping_rounds=100)
            y_pred = model.predict(df_test, num_iteration=model.best_iteration_)
            pred += y_pred
            pred /= n_fold
            bestScore = model.best_score_
            return bestScore
```

In [63]:
```
# This function will permute the value of a particular  column and run the predictive m
# The idea is to check that the prediction becomes even more worse if the column which
# shuffled.
def runPermutations(col_to_permute):
    list_score = []
    for i in range(1):
        df_train[col_to_permute] = np.random.permutation(df_train[col_to_permute])
        score = modelForPermutation()
        list_score.append(score['training']['rmse'])
    return np.mean(list_score)
```

In [73]:
```
df_train = df_train.copy()
col_to_permute = 'totals.hits'
new_score = runPermutations(col_to_permute)
```

```
Fold 0 started at Tue Oct 23 06:59:21 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[146]	training's rmse: 1.72442	valid_1's rmse: 1.5136
Fold 1 started at Tue Oct 23 06:59:23 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.50714	valid_1's rmse: 1.87035
Early stopping, best iteration is:
[548]	training's rmse: 1.49911	valid_1's rmse: 1.86999
Fold 2 started at Tue Oct 23 06:59:26 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.57004	valid_1's rmse: 1.26132
Early stopping, best iteration is:
[534]	training's rmse: 1.56552	valid_1's rmse: 1.26103
Fold 3 started at Tue Oct 23 06:59:29 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.5054	valid_1's rmse: 1.95527
Early stopping, best iteration is:
[765]	training's rmse: 1.46502	valid_1's rmse: 1.9507
Fold 4 started at Tue Oct 23 06:59:33 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.51364	valid_1's rmse: 1.88506
Early stopping, best iteration is:
[805]	training's rmse: 1.47369	valid_1's rmse: 1.88245
Fold 5 started at Tue Oct 23 06:59:37 2018
```

```
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[226]	training's rmse: 1.63848	valid_1's rmse: 1.65463
Fold 6 started at Tue Oct 23 06:59:40 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[141]	training's rmse: 1.71907	valid_1's rmse: 1.6508
Fold 7 started at Tue Oct 23 06:59:41 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.49692	valid_1's rmse: 2.07904
Early stopping, best iteration is:
[856]	training's rmse: 1.46003	valid_1's rmse: 2.07639
Fold 8 started at Tue Oct 23 06:59:45 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.48015	valid_1's rmse: 2.18975
[1000]	training's rmse: 1.41497	valid_1's rmse: 2.18668
Early stopping, best iteration is:
[941]	training's rmse: 1.4223	valid_1's rmse: 2.1857
Fold 9 started at Tue Oct 23 06:59:50 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[297]	training's rmse: 1.60662	valid_1's rmse: 1.54015
```

In [66]:
```python
col_to_permute = 'device.deviceCategory'
new_score = runPermutations(col_to_permute)
```

```
Fold 0 started at Tue Oct 23 06:47:06 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[242]	training's rmse: 1.56851	valid_1's rmse: 1.46367
Fold 1 started at Tue Oct 23 06:47:09 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.44401	valid_1's rmse: 1.82183
Early stopping, best iteration is:
[555]	training's rmse: 1.43649	valid_1's rmse: 1.82169
Fold 2 started at Tue Oct 23 06:47:12 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.49153	valid_1's rmse: 1.23012
Early stopping, best iteration is:
[506]	training's rmse: 1.4907	valid_1's rmse: 1.22998
Fold 3 started at Tue Oct 23 06:47:16 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.44766	valid_1's rmse: 1.87385
[1000]	training's rmse: 1.37049	valid_1's rmse: 1.86988
[1500]	training's rmse: 1.32083	valid_1's rmse: 1.8628
Early stopping, best iteration is:
[1471]	training's rmse: 1.32305	valid_1's rmse: 1.8626
```

```
Fold 4 started at Tue Oct 23 06:47:22 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.44259	valid_1's rmse: 1.79451
Early stopping, best iteration is:
[630]	training's rmse: 1.41304	valid_1's rmse: 1.79145
Fold 5 started at Tue Oct 23 06:47:26 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[272]	training's rmse: 1.53052	valid_1's rmse: 1.64776
Fold 6 started at Tue Oct 23 06:47:29 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[169]	training's rmse: 1.62992	valid_1's rmse: 1.61342
Fold 7 started at Tue Oct 23 06:47:31 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.42217	valid_1's rmse: 1.99666
Early stopping, best iteration is:
[666]	training's rmse: 1.39228	valid_1's rmse: 1.99315
Fold 8 started at Tue Oct 23 06:47:35 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.40253	valid_1's rmse: 2.13659
[1000]	training's rmse: 1.32006	valid_1's rmse: 2.12974
Early stopping, best iteration is:
[911]	training's rmse: 1.33323	valid_1's rmse: 2.12838
Fold 9 started at Tue Oct 23 06:47:39 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.46908	valid_1's rmse: 1.47965
Early stopping, best iteration is:
[489]	training's rmse: 1.47189	valid_1's rmse: 1.47937
```

```
In [65]: df = df_train.copy()
         col_to_permute = 'totals.pageviews'
         new_score = runPermutations(col_to_permute)
```

```
Fold 0 started at Tue Oct 23 06:46:07 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[225]	training's rmse: 1.58318	valid_1's rmse: 1.46656
Fold 1 started at Tue Oct 23 06:46:09 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.44147	valid_1's rmse: 1.82136
Early stopping, best iteration is:
[522]	training's rmse: 1.43846	valid_1's rmse: 1.82097
Fold 2 started at Tue Oct 23 06:46:12 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[282]	training's rmse: 1.56373	valid_1's rmse: 1.23643
```

```
Fold 3 started at Tue Oct 23 06:46:15 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.44826	valid_1's rmse: 1.87257
[1000]	training's rmse: 1.37811	valid_1's rmse: 1.86534
[1500]	training's rmse: 1.32274	valid_1's rmse: 1.86045
[2000]	training's rmse: 1.28461	valid_1's rmse: 1.85456
Early stopping, best iteration is:
[2026]	training's rmse: 1.28184	valid_1's rmse: 1.85411
Fold 4 started at Tue Oct 23 06:46:23 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.44838	valid_1's rmse: 1.80095
Early stopping, best iteration is:
[774]	training's rmse: 1.39929	valid_1's rmse: 1.79546
Fold 5 started at Tue Oct 23 06:46:27 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[264]	training's rmse: 1.53644	valid_1's rmse: 1.65562
Fold 6 started at Tue Oct 23 06:46:30 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[169]	training's rmse: 1.63024	valid_1's rmse: 1.6111
Fold 7 started at Tue Oct 23 06:46:32 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.42405	valid_1's rmse: 1.99841
Early stopping, best iteration is:
[634]	training's rmse: 1.40276	valid_1's rmse: 1.99637
Fold 8 started at Tue Oct 23 06:46:36 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.4054	valid_1's rmse: 2.13345
[1000]	training's rmse: 1.32871	valid_1's rmse: 2.12355
Early stopping, best iteration is:
[1095]	training's rmse: 1.32146	valid_1's rmse: 2.12311
Fold 9 started at Tue Oct 23 06:46:41 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.47042	valid_1's rmse: 1.48504
Early stopping, best iteration is:
[842]	training's rmse: 1.41176	valid_1's rmse: 1.48059
```

In [67]:
```
df = df_train.copy()
col_to_permute = 'hit_rate'
new_score = runPermutations(col_to_permute)
```

```
Fold 0 started at Tue Oct 23 06:49:40 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[137]	training's rmse: 1.73476	valid_1's rmse: 1.51699
Fold 1 started at Tue Oct 23 06:49:42 2018
```

```
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.5106	valid_1's rmse: 1.87938
Early stopping, best iteration is:
[487]	training's rmse: 1.51403	valid_1's rmse: 1.87857
Fold 2 started at Tue Oct 23 06:49:45 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.57262	valid_1's rmse: 1.26602
Early stopping, best iteration is:
[560]	training's rmse: 1.56223	valid_1's rmse: 1.26545
Fold 3 started at Tue Oct 23 06:49:48 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.50886	valid_1's rmse: 1.95223
[1000]	training's rmse: 1.43342	valid_1's rmse: 1.94335
Early stopping, best iteration is:
[1377]	training's rmse: 1.39705	valid_1's rmse: 1.93613
Fold 4 started at Tue Oct 23 06:49:55 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.51564	valid_1's rmse: 1.8884
Early stopping, best iteration is:
[620]	training's rmse: 1.49731	valid_1's rmse: 1.88632
Fold 5 started at Tue Oct 23 06:50:00 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[219]	training's rmse: 1.64514	valid_1's rmse: 1.65623
Fold 6 started at Tue Oct 23 06:50:02 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[151]	training's rmse: 1.70794	valid_1's rmse: 1.65012
Fold 7 started at Tue Oct 23 06:50:04 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.49561	valid_1's rmse: 2.08256
Early stopping, best iteration is:
[835]	training's rmse: 1.46478	valid_1's rmse: 2.07947
Fold 8 started at Tue Oct 23 06:50:09 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.47924	valid_1's rmse: 2.1885
Early stopping, best iteration is:
[830]	training's rmse: 1.43713	valid_1's rmse: 2.18484
Fold 9 started at Tue Oct 23 06:50:13 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.5438	valid_1's rmse: 1.54161
Early stopping, best iteration is:
[403]	training's rmse: 1.56767	valid_1's rmse: 1.54015
```

In [68]:
```
df = df_train.copy()
col_to_permute = 'geoNetwork.domain'
new_score = runPermutations(col_to_permute)
```

```
Fold 0 started at Tue Oct 23 06:53:51 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[135]	training's rmse: 1.73867	valid_1's rmse: 1.516
Fold 1 started at Tue Oct 23 06:53:53 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.50833	valid_1's rmse: 1.8736
Early stopping, best iteration is:
[561]	training's rmse: 1.4973	valid_1's rmse: 1.87269
Fold 2 started at Tue Oct 23 06:53:57 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.57151	valid_1's rmse: 1.26756
Early stopping, best iteration is:
[513]	training's rmse: 1.56945	valid_1's rmse: 1.26737
Fold 3 started at Tue Oct 23 06:54:01 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.50684	valid_1's rmse: 1.95105
[1000]	training's rmse: 1.43623	valid_1's rmse: 1.9424
[1500]	training's rmse: 1.39522	valid_1's rmse: 1.93612
Early stopping, best iteration is:
[1586]	training's rmse: 1.38775	valid_1's rmse: 1.93512
Fold 4 started at Tue Oct 23 06:54:08 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.51391	valid_1's rmse: 1.88741
Early stopping, best iteration is:
[656]	training's rmse: 1.49	valid_1's rmse: 1.88505
Fold 5 started at Tue Oct 23 06:54:11 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[221]	training's rmse: 1.64413	valid_1's rmse: 1.65394
Fold 6 started at Tue Oct 23 06:54:13 2018
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[151]	training's rmse: 1.70692	valid_1's rmse: 1.64887
Fold 7 started at Tue Oct 23 06:54:15 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.49371	valid_1's rmse: 2.08534
Early stopping, best iteration is:
[843]	training's rmse: 1.45755	valid_1's rmse: 2.08129
Fold 8 started at Tue Oct 23 06:54:20 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.48073	valid_1's rmse: 2.19341
Early stopping, best iteration is:
[588]	training's rmse: 1.46972	valid_1's rmse: 2.19195
Fold 9 started at Tue Oct 23 06:54:23 2018
Training until validation scores don't improve for 100 rounds.
[500]	training's rmse: 1.54301	valid_1's rmse: 1.542
Early stopping, best iteration is:
```

```
[461]	training's rmse: 1.55012	valid_1's rmse: 1.54139
```