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References

1. The json load function has been obtained from https://www.kaggle.com/kabure/exploring-the-consumer-patterns-simple-eda/notebook (https://www.kaggle.com/kabure/exploring-the-consumer-patterns-simple-eda/notebook)
2. The lightGBM function has been obtained from https://www.kaggle.com/sudalairajkumar/simple-exploration-baseline-ga-customer-revenue (https://www.kaggle.com/sudalairajkumar/simple-exploration-baseline-ga-customer-revenue)

Both these functions have been made modular and customized by the author as per the needs

Human References: Udbhav Udbhav, Nikhil Siddhartha, Vivek Kumar Sah

In [30]:

```
import pandas as pd
import numpy as np
from scipy.stats.stats import pearsonr
import matplotlib.pyplot as plt
from datetime import datetime, date
from sklearn import datasets, linear_model
from sklearn.metrics import mean_squared_error

import os # it's a operational system library, to set some informations
import random # random is to generate random values
import json
from pandas.io.json import json_normalize

import lightgbm as lgb
from sklearn import preprocessing
```

Task 0 - Data Loading

In [37]:

```
# Code to transform the json format columns in table - Obtained from Leonardo Ferre

columns = ['device', 'geoNetwork', 'totals', 'trafficSource'] # Columns that have js

# p is a fractional number to skiprows and read just a random sample of the our data
p = 1 # *** In this case we will use 50% of data set *** #

def json_read(df):
    #joining the [ path + df received]
    data_frame = df

    #Importing the dataset
    df = pd.read_csv(data_frame,
                     converters={column: json.loads for column in columns}, # loadi
                     dtype={'fullVisitorId': 'str', 'date': object, 'visitId': objec
                     skiprows=lambda i: i>0 and random.random() > p)# Number of rows

    for column in columns: #loop to finally transform the columns in data frame
        #It will normalize and set the json to a table
        column_as_df = json_normalize(df[column])
        # here will be set the name using the category and subcategory of json colu
        column_as_df.columns = [f"{column}.{subcolumn}" for subcolumn in column_as_c
        # after extracting the values, let drop the original columns
        df = df.drop(column, axis=1).merge(column_as_df, right_index=True, left_inde

    # Printing the shape of dataframes that was imported
    print(f"Loaded {os.path.basename(data_frame)}. Shape: {df.shape}")
    return df # returning the df after importing and transforming

train = json_read("train.csv")
test = json_read("test.csv")
testData.head()
```

```
Loaded train.csv. Shape: (903653, 55)
Loaded test.csv. Shape: (804684, 53)
```

Out[37]:

	channelGrouping	date	fullVisitorId	sessionId	socialEn
0	Organic Search	20171016	6167871330617112363	6167871330617112363_1508151024	Not S
1	Organic Search	20171016	0643697640977915618	0643697640977915618_1508175522	Not S
2	Organic Search	20171016	6059383810968229466	6059383810968229466_1508143220	Not S
3	Organic Search	20171016	2376720078563423631	2376720078563423631_1508193530	Not S
4	Organic Search	20171016	2314544520795440038	2314544520795440038_1508217442	Not S

5 rows × 49 columns

In [218]:

```
trainData = train
testData = test
```

Task 1 - Data Cleaning

```
I performed the following steps to clean the data

1. Remove columns which have high percentage of null values
2. Remove columns which have constant values
3. Remove columns which are not present in test dataset. Ex.
trafficSource.campaignCode
4. Remove columns which will not be used for any prediction or analysis Ex.
sessionId
5. Impute appropriate values in remaining columns which have null values

Total number of columns reduced from 55 to 24

Anamolies still existing after cleaning the dataset

1. Many string categorical columns like country, metro, etc have null, NAN or
dirty values like (not set), (not provided). Such values were not cleaned.

2. I observed that few entries had mismatch between region and city. Ex. for 1
case, city was San Francisco but region was Ireland. As such entries were very
few, they have not been cleaned.
```

In [179]:

```
# Remove columns in your model which have very large number of null values
numberOfDataPoints = trainData.shape[0];
nullCountPerColumn = trainData.isnull().sum()
percentageOfNull = (nullCountPerColumn/numberOfDataPoints) * 100
percentageOfNull.sort_values(ascending = False)
```

Out[179]:

```
trafficSource.campaignCode                         99.999889
trafficSource.adContent                            98.788694
totals.transactionRevenue                          98.725728
trafficSource.adwordsClickInfo.page                97.625195
trafficSource.adwordsClickInfo.adNetworkType       97.625195
trafficSource.adwordsClickInfo.slot                97.625195
trafficSource.adwordsClickInfo.isVideoAd           97.625195
trafficSource.adwordsClickInfo.gclId               97.614018
trafficSource.isTrueDirect                         69.678073
trafficSource.referralPath                         63.377425
trafficSource.keyword                              55.655102
totals.bounces                                     50.132407
totals.newVisits                                   22.198012
totals.pageviews                                    0.011066
device.isMobile                                     0.000000
device.flashVersion                                 0.000000
device.deviceCategory                               0.000000
device.mobileDeviceBranding                         0.000000
device.language                                     0.000000
device.browserSize                                  0.000000
device.mobileDeviceInfo                             0.000000
device.mobileDeviceMarketingName                    0.000000
device.browserVersion                               0.000000
trafficSource.source                                0.000000
device.browser                                      0.000000
visitStartTime                                      0.000000
visitNumber                                         0.000000
visitId                                             0.000000
device.mobileInputSelector                          0.000000
socialEngagementType                                0.000000
sessionId                                           0.000000
fullVisitorId                                       0.000000
date                                                0.000000
device.mobileDeviceModel                            0.000000
geoNetwork.country                                  0.000000
device.operatingSystem                              0.000000
device.operatingSystemVersion                       0.000000
trafficSource.medium                                0.000000
trafficSource.campaign                              0.000000
trafficSource.adwordsClickInfo.criteriaParameters   0.000000
totals.visits                                       0.000000
totals.hits                                         0.000000
geoNetwork.subContinent                             0.000000
geoNetwork.region                                   0.000000
geoNetwork.networkLocation                          0.000000
geoNetwork.networkDomain                            0.000000
geoNetwork.metro                                    0.000000
geoNetwork.longitude                                0.000000
geoNetwork.latitude                                 0.000000
geoNetwork.continent                                0.000000
geoNetwork.cityId                                   0.000000
```

```
geoNetwork.city                                       0.000000
device.screenResolution                               0.000000
device.screenColors                                   0.000000
channelGrouping                                       0.000000
dtype: float64
```

In [219]:

```
#drop the columns which have lots of NAN values
columnnsToBeDropped = [
                       'trafficSource.adContent',
                       'trafficSource.adwordsClickInfo.adNetworkType',
                       'trafficSource.adwordsClickInfo.slot',
                       'trafficSource.adwordsClickInfo.page',
                       'trafficSource.adwordsClickInfo.isVideoAd',
                       'trafficSource.adwordsClickInfo.gclId',
                       'trafficSource.isTrueDirect',
                       'trafficSource.referralPath',
                       'trafficSource.keyword',
                       'totals.bounces',
                       'totals.newVisits']
trainData = trainData.drop(columns = columnnsToBeDropped)
testData = testData.drop(columns = columnnsToBeDropped)

#dropping columns which are not there in test data.
trainData = trainData.drop(columns = ['trafficSource.campaignCode'])

#dropping id columns which will not be used for analysis and prediction
train_df = trainData.drop(columns = ['sessionId'])
test_df = testData.drop(columns = ['sessionId'])

print(trainData.shape)
print(testData.shape)
```

```
(903653, 43)
(804684, 42)
```

In [5]:

```
# There are 12 columns having large number of null values. We will do further analys
trainData.nunique().sort_values()
```

Out[5]:

```
device.operatingSystemVersion                           1
geoNetwork.cityId                                       1
device.mobileInputSelector                              1
device.mobileDeviceModel                                1
device.mobileDeviceMarketingName                        1
device.mobileDeviceInfo                                 1
device.mobileDeviceBranding                             1
device.language                                         1
device.flashVersion                                     1
device.screenColors                                     1
device.screenResolution                                 1
device.browserSize                                      1
geoNetwork.latitude                                     1
geoNetwork.longitude                                    1
geoNetwork.networkLocation                              1
socialEngagementType                                    1
totals.visits                                           1
trafficSource.adwordsClickInfo.criteriaParameters       1
device.browserVersion                                   1
device.isMobile                                         2
device.deviceCategory                                   3
geoNetwork.continent                                    6
trafficSource.medium                                    7
trafficSource.campaign                                  8
channelGrouping                                         8
device.operatingSystem                                 17
geoNetwork.subContinent                                23
device.browser                                         40
geoNetwork.metro                                       84
totals.pageviews                                      142
totals.hits                                           190
geoNetwork.country                                    201
trafficSource.source                                  222
visitNumber                                           256
geoNetwork.region                                     359
date                                                  366
geoNetwork.city                                       597
totals.transactionRevenue                            1469
geoNetwork.networkDomain                            11178
fullVisitorId                                      165800
visitId                                            179935
visitStartTime                                     179962
sessionId                                          180566
dtype: int64
```

In [220]:

```
# Remove those columns for which the unique count is 1
columnWithUniqueCountAs1 = [column for column in trainData.columns if trainData[colu
trainData.drop(columnWithUniqueCountAs1, axis=1, inplace=True)
testData.drop(columnWithUniqueCountAs1, axis=1, inplace=True)
print(trainData.shape)
print(testData.shape)
```

```
(903653, 24)
(804684, 23)
```

In [221]:

```
#Fill NaN values with some default values
trainData["totals.transactionRevenue"] = trainData["totals.transactionRevenue"].fill
trainData['totals.pageviews'].fillna(1, inplace=True)
testData['totals.pageviews'].fillna(1, inplace=True)
trainData['totals.hits'].fillna(1, inplace=True)
testData['totals.hits'].fillna(1, inplace=True)

trainData['totals.pageviews'] = trainData['totals.pageviews'].astype(int)
trainData["totals.hits"] = trainData["totals.hits"].astype(float)
testData['totals.pageviews'] = testData['totals.pageviews'].astype(int)
testData["totals.hits"] = testData["totals.hits"].astype(float)
```

In [222]:

```
# Creating additional columns

# 1. Create a new column visit_day from date
def getDayOfVisit(x):
    return datetime.strptime(x, '%Y%m%d').day
trainData['visit_day'] = trainData['date'].map(getDayOfVisit)
testData['visit_day'] = testData['date'].map(getDayOfVisit)

# 2. Create a new column visit_month from date
def getMonthOfVisit(x):
    return datetime.strptime(x, '%Y%m%d').month
trainData['visit_month'] = trainData['date'].map(getMonthOfVisit)
testData['visit_month'] = testData['date'].map(getMonthOfVisit)

# 3. Create a new column visit_day from date
def getYearOfVisit(x):
    return datetime.strptime(x, '%Y%m%d').year
trainData['visit_year'] = trainData['date'].map(getYearOfVisit)
testData['visit_year'] = testData['date'].map(getYearOfVisit)

# 4. Create a new column visit_hour from visitStartTime
def getHourOfVisit(x):
    ts = int(x)
    return datetime.utcfromtimestamp(ts).hour
trainData['visit_hour'] = trainData['visitStartTime'].map(getHourOfVisit)
testData['visit_hour'] = testData['visitStartTime'].map(getHourOfVisit)

# 5. Create a new column visit_hour from visitStartTime
def getMinutesOfVisit(x):
    ts = int(x)
    return datetime.utcfromtimestamp(ts).minute
trainData['visit_minute'] = trainData['visitStartTime'].map(getMinutesOfVisit)
testData['visit_minute'] = testData['visitStartTime'].map(getMinutesOfVisit)

# 6. Create a new column visit_hour from visitStartTime
def getSecondsOfVisit(x):
    ts = int(x)
    return datetime.utcfromtimestamp(ts).second
trainData['visit_second'] = trainData['visitStartTime'].map(getSecondsOfVisit)
testData['visit_second'] = testData['visitStartTime'].map(getSecondsOfVisit)

# 7. Create a new column visit_week from date
def getWeekDayOfVisitDate(x):
    return datetime.strptime(x, '%Y%m%d').weekday()
trainData['visit_week'] = trainData['date'].map(getWeekDayOfVisitDate)
testData['visit_week'] = testData['date'].map(getWeekDayOfVisitDate)

print(trainData.shape)
print(testData.shape)
```

```
(903653, 31)
(804684, 30)
```

Task 2 - 3 plots for correlations

In [224]:

```
#Before taking correlation remove all rows where transaction revenue is 0 or NULL

#y = trainData[trainData["totals.transactionRevenue"] >= 0.01]
correlation = trainData.corr(method='pearson')
correlation.style.format("{:.2}").background_gradient(cmap=plt.get_cmap('RdYlGn'), a
```

Out[224]:

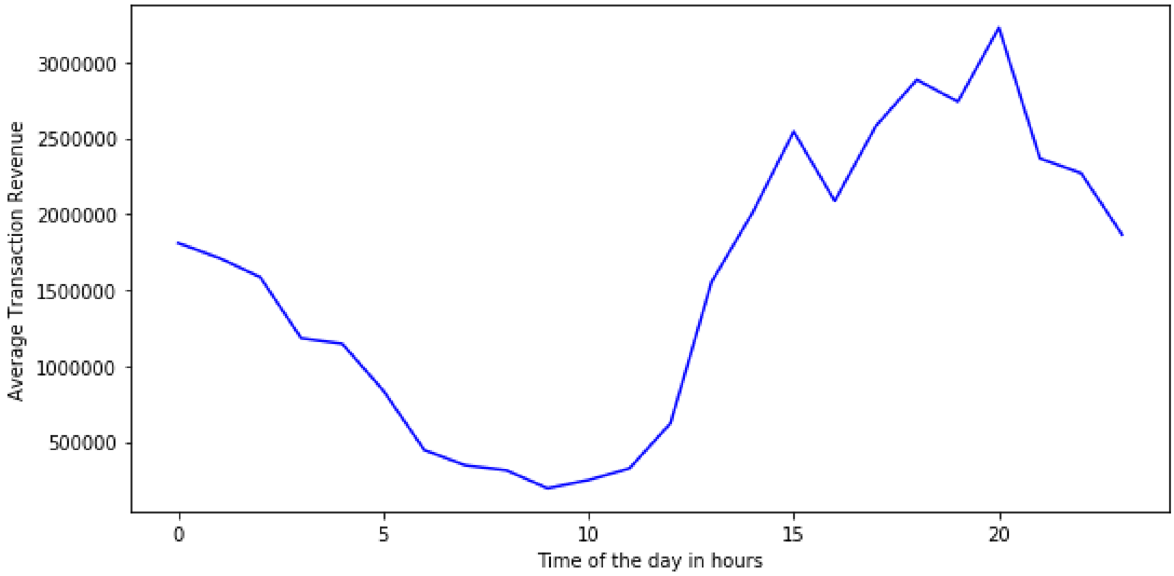
	visitNumber	device.isMobile	totals.hits	totals.pageviews	totals.transa
visitNumber	1.0	-0.038	0.041	0.043	
device.isMobile	-0.038	1.0	-0.03	-0.03	
totals.hits	0.041	-0.03	1.0	0.98	
totals.pageviews	0.043	-0.03	0.98	1.0	
totals.transactionRevenue	0.051	-0.017	0.15	0.16	
visit_day	-0.0028	0.0017	-0.005	-0.0048	
visit_month	-0.011	-0.11	0.0031	-0.0023	
visit_year	0.0079	0.14	-0.018	-0.011	
visit_hour	0.025	-0.025	0.017	0.019	
visit_minute	-0.0014	-0.0021	-0.0027	-0.0027	
visit_second	-0.0014	-0.0035	-0.00059	-0.00064	
visit_week	-0.02	0.079	-0.012	-0.012	

1. Time of the day in hours vs Average Transaction Revenue

The time is calculated as UTC timestamp. The plot gives us an idea that people are more active

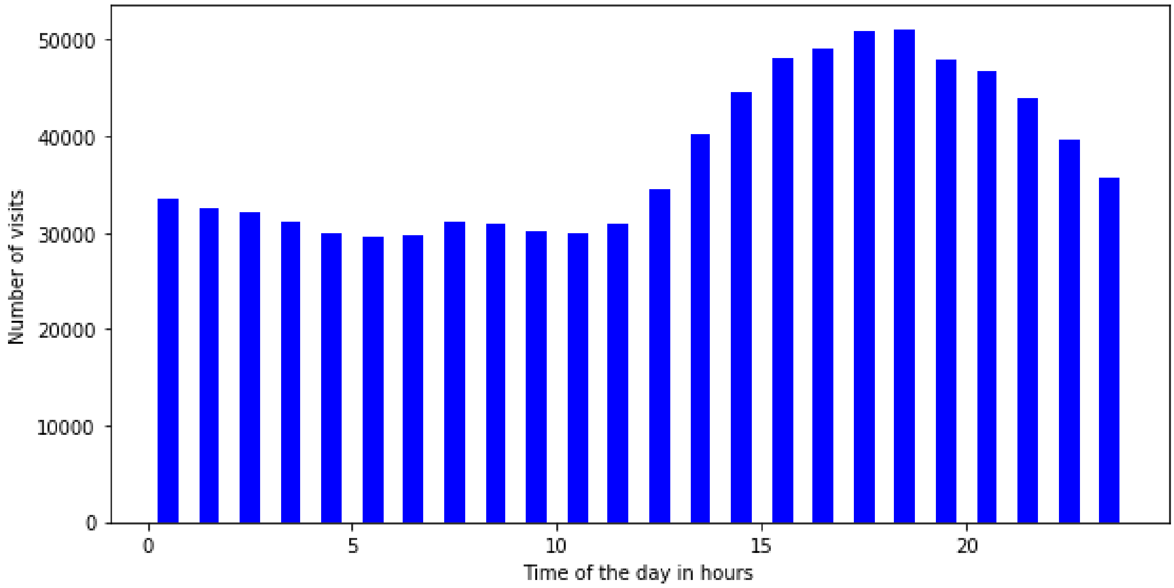
In [225]:

```
groupby_visit_hour = trainData.groupby(['visit_hour']).mean()
plt.plot(groupby_visit_hour['totals.transactionRevenue'], color='blue')
plt.xlabel('Time of the day in hours')
plt.ylabel('Average Transaction Revenue')
plt.show()
```



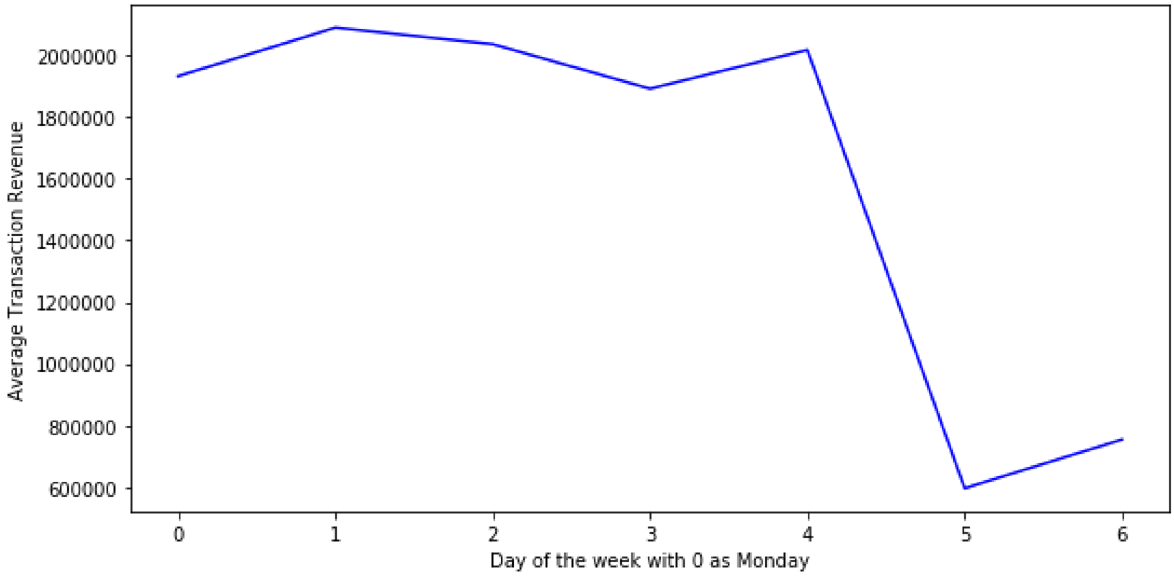
In [226]:

```
plt.hist(trainData['visit_hour'], color='blue', rwidth=0.5, bins=np.arange(trainData
plt.xlabel('Time of the day in hours')
plt.ylabel('Number of visits')
plt.show()
```



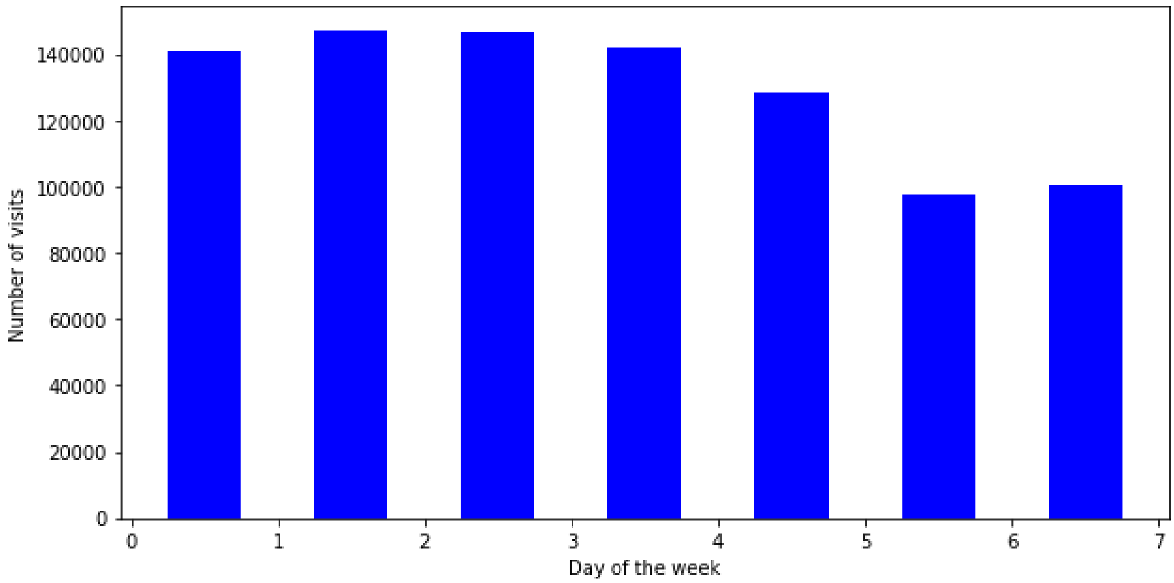
In [227]:

```
groupby_visit_weekday = trainData.groupby(['visit_week']).mean()
plt.plot(groupby_visit_weekday['totals.transactionRevenue'], color='blue')
plt.xlabel('Day of the week with 0 as Monday')
plt.ylabel('Average Transaction Revenue')
plt.show()
```



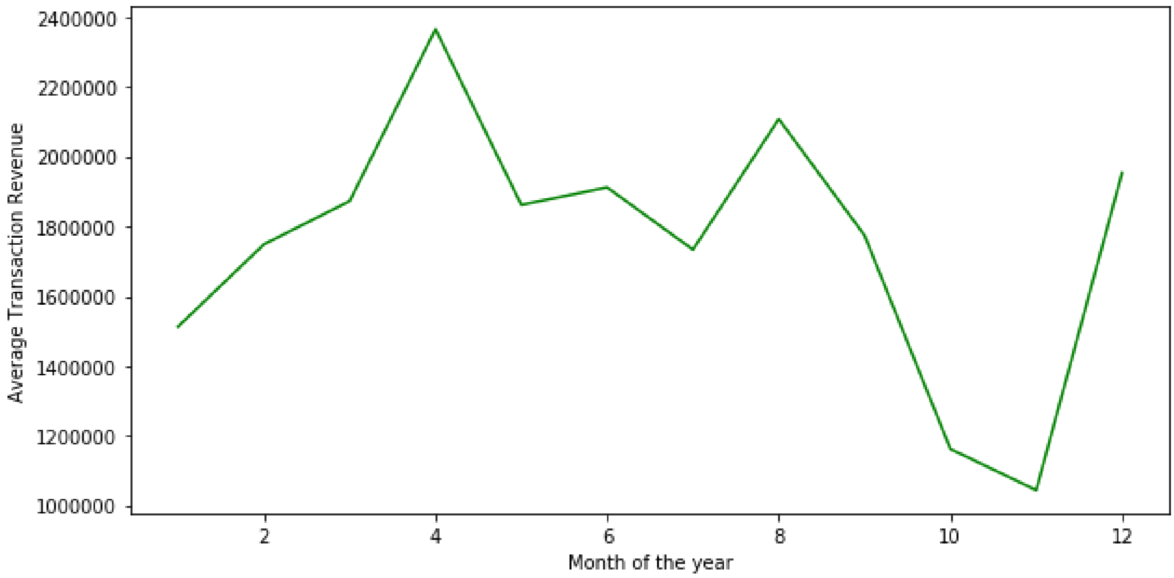
In [228]:

```
plt.hist(trainData['visit_week'], color='blue', rwidth=0.5, bins=np.arange(trainData
plt.xlabel('Day of the week')
plt.ylabel('Number of visits')
plt.show()
```



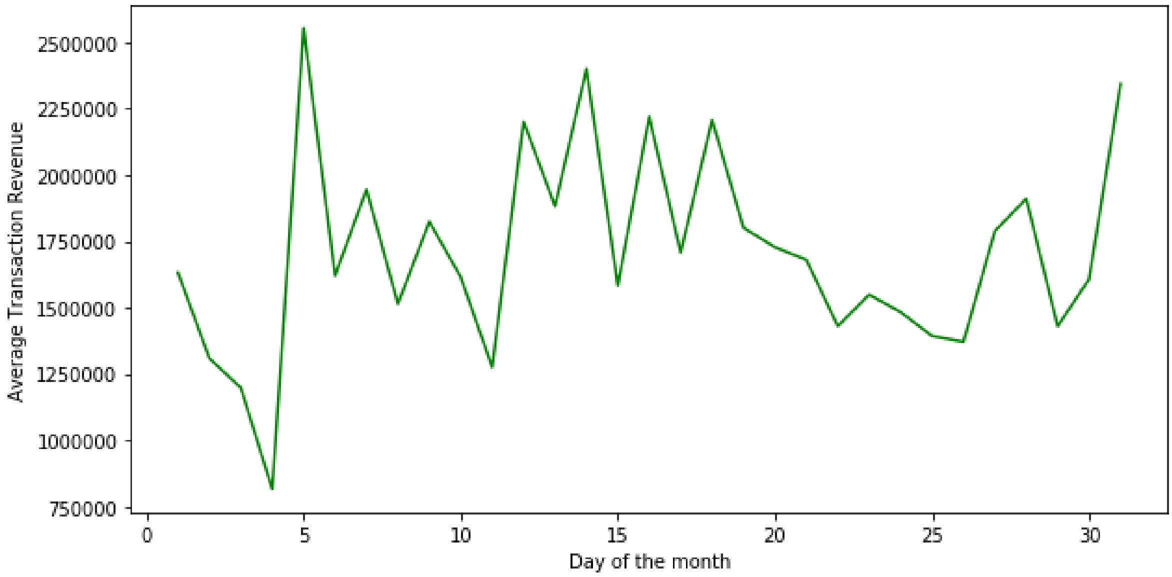
In [229]:

```
groupby_visit_month = trainData.groupby(['visit_month']).mean()
plt.plot(groupby_visit_month['totals.transactionRevenue'], color='green')
plt.xlabel('Month of the year')
plt.ylabel('Average Transaction Revenue')

plt.show()
```



In [230]:

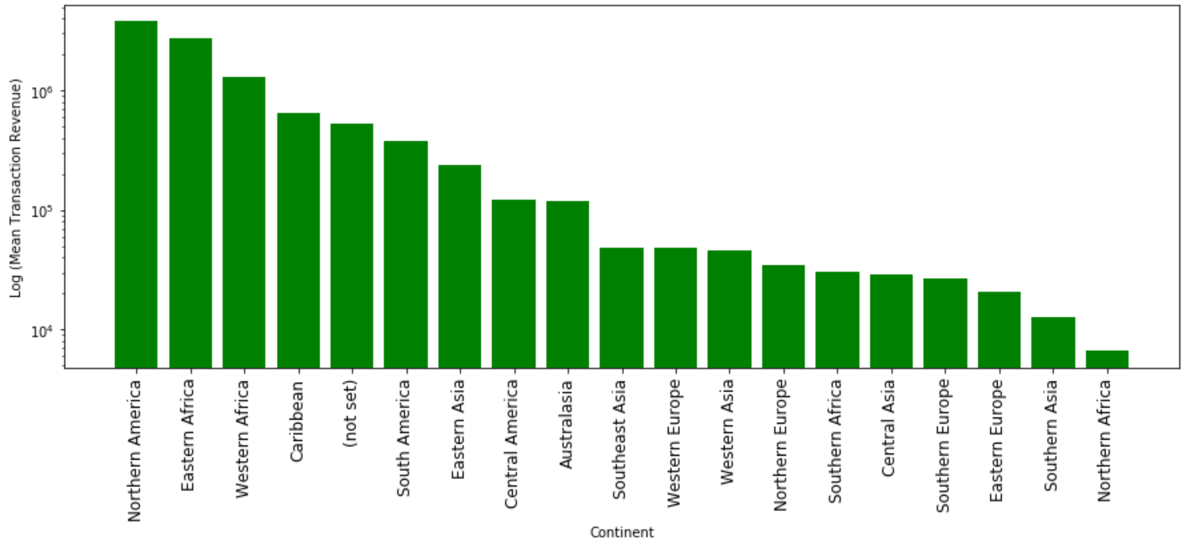
```
groupby_visit_day = trainData.groupby(['visit_day']).mean()
plt.plot(groupby_visit_day['totals.transactionRevenue'], color='green')
plt.xlabel('Day of the month')
plt.ylabel('Average Transaction Revenue')

plt.show()
```

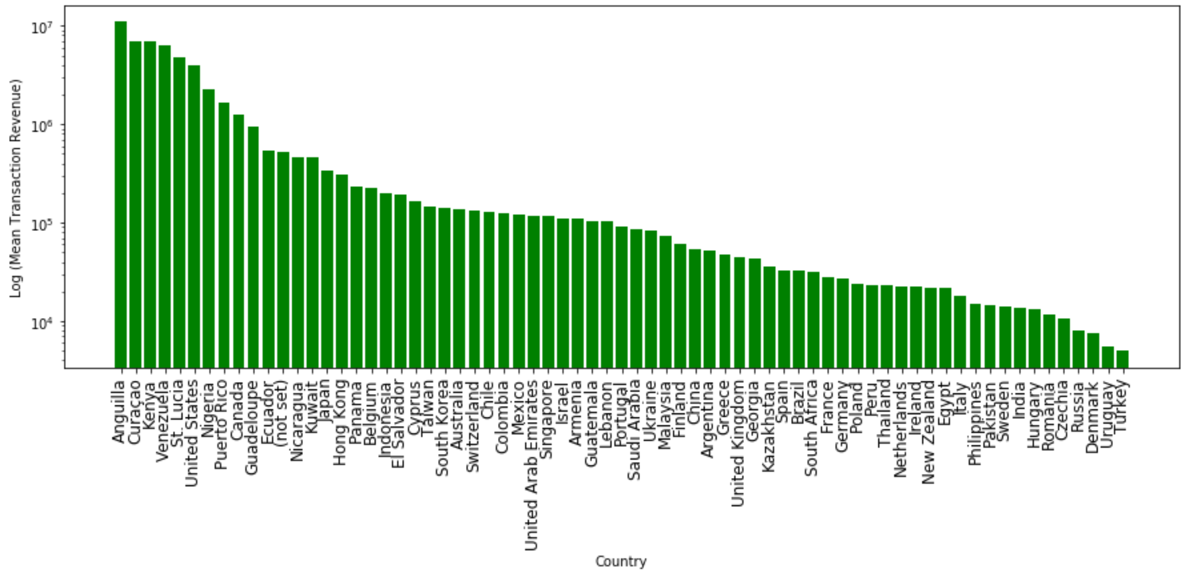


Task 3 - Cluster the variables with geographic info available

In [232]:

```
# plotABarChart function -  obtained from Udbhav Kernel
def plotABarChart(xKeys, y, xLabel, yLabel, log = False, figsize = [15.0, 5.0], rot=
    x = np.arange(xKeys.shape[0])
    plt.rcParams['figure.figsize'] = figsize
    plt.bar(x, y, log = log, color="green")
    plt.ylabel(yLabel)
    plt.xlabel(xLabel)
    plt.xticks(x, xKeys, fontsize=12, rotation=rot)
    plt.show()

subContinents = trainData.groupby("geoNetwork.subContinent").mean().reset_index()
subContinents = subContinents[subContinents["totals.transactionRevenue"] > 0]
subContinents = subContinents.sort_values(by=['totals.transactionRevenue'], ascendin
plotABarChart(subContinents["geoNetwork.subContinent"].values, subContinents["totals

countries = trainData.groupby("geoNetwork.country").mean().reset_index()
countries = countries[countries["totals.transactionRevenue"] > 0]
countries = countries.sort_values(by=['totals.transactionRevenue'], ascending = Fals
plotABarChart(countries["geoNetwork.country"].values, countries["totals.transaction
```





Task 4 - Define a buying score for each user

1. Logistic Regression Model - Decide the features and binary class for logistic regression model

In [233]:

```
trainLR = trainData

columnsForOneHotEncoding = ['device.deviceCategory', 'device.isMobile', 'geoNetwork.
X = trainLR[columnsForOneHotEncoding]
X = pd.get_dummies(X, columns=columnsForOneHotEncoding)
X['totals.pageviews'] = trainData['totals.pageviews']
X['totals.hits'] = trainData['totals.hits']
X['visit_year'] = trainData['visit_year']
X['visit_month'] = trainData['visit_month']
X['visit_day'] = trainData['visit_day']
X['visit_hour'] = trainData['visit_hour']
X['visit_minute'] = trainData['visit_minute']
X['visit_second'] = trainData['visit_second']
X['visitNumber'] = trainData['visitNumber']

def doesUserBuy(x):
    return 1 if x > 0.001 else 0
Y = pd.DataFrame()
Y['doesUserBuy'] = trainLR['totals.transactionRevenue'].map(doesUserBuy)
```

2. Split train data into training set and validation set so that accuracy of logistic regression model can be calculated on validation data

In [234]:

```
# Split the train dataset into development and valid based on time
perm = np.random.permutation(X.index)
m = len(X.index)
train_end = int(0.8 * m)
test_end = int(0.2 * m) + train_end

X_train = X.iloc[perm[:train_end]]
X_test = X.iloc[perm[train_end:test_end]]

Y_train = Y.iloc[perm[:train_end]]
Y_test = Y.iloc[perm[train_end:test_end]]

Id_Train = trainLR["fullVisitorId"][perm[:train_end]]
Id_Test = trainLR["fullVisitorId"][perm[train_end:test_end]]

Revenue_Train = trainLR['totals.transactionRevenue'][perm[:train_end]]
Revenue_Test = trainLR['totals.transactionRevenue'][perm[train_end:test_end]]

X_train.reset_index(drop=True, inplace=True)
X_test.reset_index(drop=True, inplace=True)
Y_train.reset_index(drop=True, inplace=True)
Y_test.reset_index(drop=True, inplace=True)
Id_Train.reset_index(drop=True, inplace=True)
Id_Test.reset_index(drop=True, inplace=True)
Revenue_Train.reset_index(drop=True, inplace=True)
Revenue_Test.reset_index(drop=True, inplace=True)

Id_Test.head(10)
```

Out[234]:

```
0     962968224722344719
1    9839034753807489913
2    9637023476808058644
3    0166714065624374803
4    9973571671481160644
5    3300622118189485946
6    0012021439019164032
7    9444968272609420975
8     403124097952602818
9    8355729127276599774
Name: fullVisitorId, dtype: object
```

3. Train the model, predict and calculate probabilities

In [235]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

logreg = LogisticRegression(solver='lbfgs')
logreg.fit(X_train, Y_train)

probabilities = logreg.predict_proba(X_test)
trainMeanAcc = logreg.score(X_train, Y_train)
valMeanAcc = accuracy_score(Y_test["doesUserBuy"], logreg.predict(X_test))

print("Train Mean Accuracy For Logistic Regression On Randomly Sampled Train Data ",
print("Validation Mean Accuracy For Logistic Regression On Randomly Sampled Validat
buying_score = pd.concat([Id_Test, Revenue_Test, Y_test["doesUserBuy"], pd.DataFrame
buying_score.sort_values(by=1, ascending=False).head(10)
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:57
8: DataConversionWarning: A column-vector y was passed when a 1d array
was expected. Please change the shape of y to (n_samples, ), for examp
le using ravel().
  y = column_or_1d(y, warn=True)

Train Mean Accuracy For Logistic Regression On Randomly Sampled Train
Data  0.9866278796329341
Validation Mean Accuracy For Logistic Regression On Randomly Sampled V
alidation Data  0.9865268632767111
```

Out[235]:

	fullVisitorId	totals.transactionRevenue	doesUserBuy	0	1
111103	6879336706336070910	1.339500e+08	1	0.000000e+00	1.000000
51657	9264804092676520813	1.520530e+09	1	0.000000e+00	1.000000
89541	4636052301667930460	0.000000e+00	0	7.771561e-15	1.000000
90724	743123551680199202	1.038200e+08	1	1.421085e-14	1.000000
170663	9634718394347160889	2.504300e+08	1	7.487975e-09	1.000000
143805	1106901861011569877	0.000000e+00	0	4.108179e-08	1.000000
12443	7480579182178358481	2.695000e+07	1	3.890673e-07	1.000000
38290	2026495143571924795	0.000000e+00	0	1.343741e-06	0.999999
90315	3979618861854336423	1.890180e+09	1	2.247271e-06	0.999998
99083	127019947788366078	2.793000e+07	1	4.554559e-06	0.999995

```
Approach
I have split training data into 80% training data and 20% validation data.
I have taken all numerical columns and few categorical columns so that the model
could be trained in a reasonable time. I have considered 2 classes
a.) 1 when transaction revenue exists
b.) 0 when transaction revenue does not exist

Analysis

After running the model, we find that training accuracy and validation accuracy
are very high (98%) and almost equal. Ideally, validation accuracy should have
been less than training accuracy.
```

```
This is happening because of imbalanced dataset. Most of the data in training and
testing set belong to class 0.

COnclusion
For top 10, 6 out of 4 values are correctly classified. This unbalanced dataset
issue can be resolved if we provide some weight to class with lower frequency.
Another great way to fix this would be to use Light Gradient Boost Model which we
have explored in the next section.
```

Task 5 - Identify external data set

Dataset 1 - https://timezonedb.com/ (https://timezonedb.com/) The given dataset has given all the datapoints in UTC timezone. In order to analyze revenue in a particular geographical area, timezones would be an extremely useful feature. Dataset 1 gives free time zone database for cities of the world. This can be easily incorporated.

Dataset 2 - https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD (https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD) In general, countries with higher GDP have high chances of buying products online. Thus analysing data of a particular country and correlating with GDP could give a lot of insightful info.

Task 6 - Build the prediction model for kaggle

In [236]:

```
# References - This piece is modified version of SRK Kernel obtained on Kaggle
train_df = trainData
test_df = testData
train_id = train_df["fullVisitorId"].values
test_id = test_df["fullVisitorId"].values

cat_cols = ["device.browser",
            "device.deviceCategory",
            "device.operatingSystem",
            "trafficSource.source",
            "trafficSource.medium",
            "trafficSource.campaign",
            "geoNetwork.continent",
            "geoNetwork.subContinent",
            "geoNetwork.country",
            "geoNetwork.city",
            "geoNetwork.metro",
            "geoNetwork.region",
            "channelGrouping",
            "geoNetwork.networkDomain"]


for col in cat_cols:
    print(col)
    lbl = preprocessing.LabelEncoder()
    lbl.fit(list(train_df[col].values.astype('str')) + list(test_df[col].values.asty
    train_df[col] = lbl.transform(list(train_df[col].values.astype('str')))
    test_df[col] = lbl.transform(list(test_df[col].values.astype('str')))

num_cols = ["totals.hits", "totals.pageviews", "visitNumber", "visit_year", "visit_c
for col in num_cols:
    train_df[col] = train_df[col].astype(float)
    test_df[col] = test_df[col].astype(float)
```

```
device.browser
device.deviceCategory
device.operatingSystem
trafficSource.source
trafficSource.medium
trafficSource.campaign
geoNetwork.continent
geoNetwork.subContinent
geoNetwork.country
geoNetwork.city
geoNetwork.metro
geoNetwork.region
channelGrouping
geoNetwork.networkDomain
```

In [241]:

```
# Split the train dataset into development and valid based on time

def getTrainTestPermuteForDataframeIndex(df, trainFraction, testFraction):
    dfSize = len(df.index)
    perm = np.random.permutation(df.index)
    trainEnd = int(trainFraction * dfSize)
    validateEnd = int(testFraction * dfSize) + trainEnd
    return perm[:train_end], perm[train_end:validate_end]

permutedTrainIndexArr, permutedTestIndexArr = getTrainTestPermuteForDataframeIndex(t

dev_df = train_df.iloc[permutedTrainIndexArr]
val_df = train_df.iloc[permutedTestIndexArr]
dev_y = np.log1p(dev_df["totals.transactionRevenue"].values)
val_y = np.log1p(val_df["totals.transactionRevenue"].values)

dev_X = dev_df[cat_cols + num_cols]
val_X = val_df[cat_cols + num_cols]
test_X = test_df[cat_cols + num_cols]
```

In [242]:

```
# custom function to run light gbm model
def run_lgb(train_X, train_y, val_X, val_y, test_X):
    params = {
        "objective" : "regression",
        "metric" : "rmse",
        "num_leaves" : 30,
        "min_child_samples" : 100,
        "learning_rate" : 0.1,
        "bagging_fraction" : 0.7,
        "feature_fraction" : 0.5,
        "bagging_frequency" : 5,
        "bagging_seed" : 2018,
        "verbosity" : -1
    }

    lgtrain = lgb.Dataset(train_X, label=train_y)
    lgval = lgb.Dataset(val_X, label=val_y)
    model = lgb.train(params, lgtrain, 1000, valid_sets=[lgval], early_stopping_rour

    pred_test_y = model.predict(test_X, num_iteration=model.best_iteration)
    pred_val_y = model.predict(val_X, num_iteration=model.best_iteration)
    return pred_test_y, model, pred_val_y

# Training the model #
pred_test, model, pred_val = run_lgb(dev_X, dev_y, val_X, val_y, test_X)
```

```
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.63648
[200]   valid_0's rmse: 1.62805
[300]   valid_0's rmse: 1.62509
[400]   valid_0's rmse: 1.62598
Early stopping, best iteration is:
[315]   valid_0's rmse: 1.62482
```

In [244]:

```
from sklearn import metrics

def getMSEOnLGBM(pred_val, val_df):
    pred_val[pred_val<0] = 0
    val_pred_df = pd.DataFrame({"fullVisitorId":val_df["fullVisitorId"].values})
    val_pred_df["transactionRevenue"] = val_df["totals.transactionRevenue"].values
    val_pred_df["PredictedRevenue"] = np.expm1(pred_val)
    val_pred_df = val_pred_df.groupby("fullVisitorId")["transactionRevenue", "Predic
    mse = np.sqrt(metrics.mean_squared_error(np.log1p(val_pred_df["transactionRevenu
    return mse

normalMse = getMSEOnLGBM(pred_val, val_df)
print(normalMse)
```

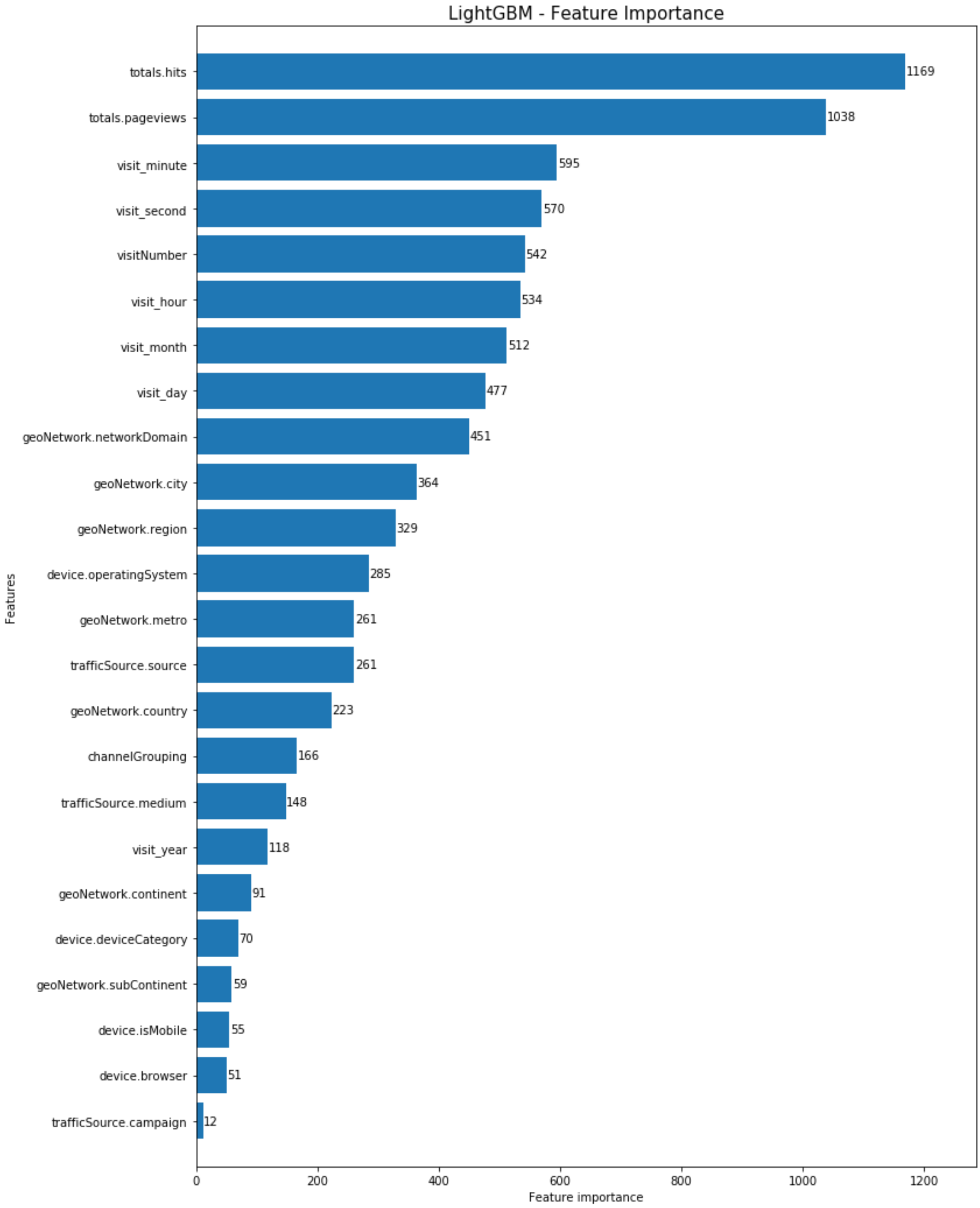
```
1.6201535091464907
```

In [204]:

```
sub_df = pd.DataFrame({"fullVisitorId":test_id})
pred_test[pred_test<0] = 0
sub_df["PredictedLogRevenue"] = np.expm1(pred_test)
sub_df = sub_df.groupby("fullVisitorId")["PredictedLogRevenue"].sum().reset_index()
sub_df.columns = ["fullVisitorId", "PredictedLogRevenue"]
sub_df["PredictedLogRevenue"] = np.log1p(sub_df["PredictedLogRevenue"])
sub_df.to_csv("baseline_lgb.csv", index=False)
```

In [205]:

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



Task 7 - Perform a permutation test

In [240]:

```
def permutationTest(dev_X, dev_y, val_X, val_y, test_X, iterations, featureToBePermu

    mseListAfterPermutation = []
    for i in range(1,iterations+1):
        copy_dev_X = dev_X.copy()
        copy_dev_X[featureToBePermuted] = np.random.permutation(copy_dev_X[featureTo
        copy_dev_X[featureToBePermuted] = copy_dev_X[featureToBePermuted].astype(flo
        pred_test, model, pred_val = run_lgb(copy_dev_X, dev_y, val_X, val_y, test_X
        mse = getMSEOnLGBM(pred_val, val_df)
        mseListAfterPermutation.append(mse)
        print(mse)
    return mseListAfterPermutation

mseListSignificantFeaturePermut = permutationTest(dev_X, dev_y, val_X, val_y, test_X
mseListForNotSignificantFeaturePermut = permutationTest(dev_X, dev_y, val_X, val_y,

print("Normal MSE ", normalMse)
print("Trying for significant feature: Hits")
print(mseListSignificantFeaturePermut)
print("Trying for not so significant feature: trafficSource.campaign")
print(mseListForNotSignificantFeaturePermut)
```

```
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.66438
[200]   valid_0's rmse: 1.66356
Early stopping, best iteration is:
[139]   valid_0's rmse: 1.6624
1.6663498257646165
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.66404
[200]   valid_0's rmse: 1.66222
Early stopping, best iteration is:
[172]   valid_0's rmse: 1.66168
1.6648824378228155
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.66436
[200]   valid_0's rmse: 1.66435
Early stopping, best iteration is:
[150]   valid_0's rmse: 1.66332
1.6669597647471286
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.66392
[200]   valid_0's rmse: 1.6618
Early stopping, best iteration is:
[188]   valid_0's rmse: 1.66166
1.6661943743200456
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.66455
[200]   valid_0's rmse: 1.66423
Early stopping, best iteration is:
[153]   valid_0's rmse: 1.66324
1.6671853771597325
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.66571
[200]   valid_0's rmse: 1.66489
Early stopping, best iteration is:
[136]   valid_0's rmse: 1.66414
1.667432608525147
```

```
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.66151
[200]   valid_0's rmse: 1.66074
Early stopping, best iteration is:
[156]   valid_0's rmse: 1.65976
1.6642110681717213
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.66387
[200]   valid_0's rmse: 1.66361
Early stopping, best iteration is:
[146]   valid_0's rmse: 1.66302
1.666045714231916
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.66237
[200]   valid_0's rmse: 1.66133
Early stopping, best iteration is:
[149]   valid_0's rmse: 1.66052
1.6645021773961735
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.66387
[200]   valid_0's rmse: 1.66246
Early stopping, best iteration is:
[169]   valid_0's rmse: 1.66227
1.6649321728556281
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.63781
[200]   valid_0's rmse: 1.63175
[300]   valid_0's rmse: 1.63147
Early stopping, best iteration is:
[242]   valid_0's rmse: 1.63108
1.6337391088265925
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.63801
[200]   valid_0's rmse: 1.63339
[300]   valid_0's rmse: 1.63226
Early stopping, best iteration is:
[290]   valid_0's rmse: 1.63205
1.6343591076134831
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.63991
[200]   valid_0's rmse: 1.63354
[300]   valid_0's rmse: 1.63161
Early stopping, best iteration is:
[286]   valid_0's rmse: 1.63108
1.6336357079811992
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.63964
[200]   valid_0's rmse: 1.63301
[300]   valid_0's rmse: 1.63073
Early stopping, best iteration is:
[295]   valid_0's rmse: 1.63063
1.6332647734476287
Training until validation scores don't improve for 100 rounds.
[100]   valid_0's rmse: 1.63907
[200]   valid_0's rmse: 1.63357
[300]   valid_0's rmse: 1.63114
[400]   valid_0's rmse: 1.6322
Early stopping, best iteration is:
[303]   valid_0's rmse: 1.63083
1.6326897532939448
Training until validation scores don't improve for 100 rounds.
```

```
[100]	valid_0's rmse: 1.63992
[200]	valid_0's rmse: 1.63335
[300]	valid_0's rmse: 1.63148
Early stopping, best iteration is:
[252]	valid_0's rmse: 1.63133
1.63472430306656
Training until validation scores don't improve for 100 rounds.
[100]	valid_0's rmse: 1.63965
[200]	valid_0's rmse: 1.63363
[300]	valid_0's rmse: 1.63157
Early stopping, best iteration is:
[257]	valid_0's rmse: 1.63087
1.6339592576036814
Training until validation scores don't improve for 100 rounds.
[100]	valid_0's rmse: 1.63725
[200]	valid_0's rmse: 1.63145
[300]	valid_0's rmse: 1.62986
Early stopping, best iteration is:
[253]	valid_0's rmse: 1.62946
1.6323021767086747
Training until validation scores don't improve for 100 rounds.
[100]	valid_0's rmse: 1.63982
[200]	valid_0's rmse: 1.63466
[300]	valid_0's rmse: 1.63336
Early stopping, best iteration is:
[257]	valid_0's rmse: 1.63292
1.6354638631420542
Training until validation scores don't improve for 100 rounds.
[100]	valid_0's rmse: 1.63788
[200]	valid_0's rmse: 1.63196
[300]	valid_0's rmse: 1.63009
Early stopping, best iteration is:
[284]	valid_0's rmse: 1.62965
1.6323982036397526
Normal MSE  1.6668881088000314
Trying for significant feature: Hits
[1.6663498257646165, 1.6648824378228155, 1.6669597647471286, 1.6661943
743200456, 1.6671853771597325, 1.667432608525147, 1.6642110681717213,
1.666045714231916, 1.6645021773961735, 1.6649321728556281]
Trying for not so significant feature: trafficSource.campaign
[1.6337391088265925, 1.6343591076134831, 1.6336357079811992, 1.6332647
734476287, 1.6326897532939448, 1.63472430306656, 1.6339592576036814,
1.6323021767086747, 1.6354638631420542, 1.6323982036397526]
```

In [245]:

```python
print("Normal MSE ", normalMse)
```

```
Normal MSE  1.6201535091464907
```

In [ ]:

```

```