

# EDA and Data Cleaning

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## 1 EDA and Data Cleaning

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```
In [1]: #Importing libraries
import zipfile
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
# Input data files are available in the "../input/" directory.
import os
import matplotlib.pyplot as plt#visualization
from PIL import Image
%matplotlib inline
import pandas as pd
import seaborn as sns#visualization
import itertools
import warnings
warnings.filterwarnings("ignore")
import io
import plotly.offline as py#visualization
py.init_notebook_mode(connected=True)#visualization
import plotly.graph_objs as go#visualization
import plotly.tools as tls#visualization
import plotly.figure_factory as ff#visualization
```

```
import plotly.express as px

start_time = pd.datetime.now()
```

## 2 1.Data

### 2.1 1.1.Data Overview

```
In [3]: %%time
        #load file from local zip
        zf = zipfile.ZipFile('expedia-hotel-recommendations.zip')
        df = pd.read_csv(zf.open('train.csv'))
```

CPU times: user 1min 27s, sys: 43.7 s, total: 2min 11s  
Wall time: 2min 34s

```
In [5]: #load file from s3 with pyspark
        '''
        def read_csv_s3(path):
            import os
            from pyspark.sql import SparkSession
            AWS_USER = os.environ.get('AWSUSER')
            AWS_PASSWORD = os.environ.get('AWSPASSWORD')
            os.environ['PYSPARK_SUBMIT_ARGS'] = ("--packages=org.apache.hadoop:hadoop-aws:2.7.0")
            spark = SparkSession.builder.appName('S3CSVRead').getOrCreate()
            spark._jsc.hadoopConfiguration().set("fs.s3a.impl", "org.apache.hadoop.fs.s3native")
            spark._jsc.hadoopConfiguration().set("fs.s3a.awsAccessKeyId", AWS_USER)
            spark._jsc.hadoopConfiguration().set("fs.s3a.awsSecretAccessKey", AWS_PASSWORD)
            df= spark.read.csv(path, header=True)
            return df,spark
        '''
```

```
In [6]: #%%time
        #path="s3a://593research/train.csv"
        #df,spark = read_csv_s3()
```

CPU times: user 2.86 ms, sys: 1.68 ms, total: 4.54 ms  
Wall time: 567 ms

```
In [168]: len(df)
```

```
Out[168]: 37670293
```

```
In [4]: df.head()
```

```
Out[4]:
```

	date_time	site_name	posa_continent	user_location_country	\
0	2014-08-11 07:46:59	2	3	66	

1	2014-08-11 08:22:12	2	3	66
2	2014-08-11 08:24:33	2	3	66
3	2014-08-09 18:05:16	2	3	66
4	2014-08-09 18:08:18	2	3	66

	user_location_region	user_location_city	orig_destination_distance	\
0	348	48862	2234.2641	
1	348	48862	2234.2641	
2	348	48862	2234.2641	
3	442	35390	913.1932	
4	442	35390	913.6259	

	user_id	is_mobile	is_package	...	srch_children_cnt	srch_rm_cnt	\
0	12	0	1	...	0	1	
1	12	0	1	...	0	1	
2	12	0	0	...	0	1	
3	93	0	0	...	0	1	
4	93	0	0	...	0	1	

	srch_destination_id	srch_destination_type_id	is_booking	cnt	\
0	8250	1	0	3	
1	8250	1	1	1	
2	8250	1	0	1	
3	14984	1	0	1	
4	14984	1	0	1	

	hotel_continent	hotel_country	hotel_market	hotel_cluster
0	2	50	628	1
1	2	50	628	1
2	2	50	628	1
3	2	50	1457	80
4	2	50	1457	21

[5 rows x 24 columns]

```
In [173]: #randomly sample 1% from training dataset for data manipulation and training
data = df.sample(frac=0.01, random_state=99)
```

```
In [174]: %%time
```

```
print ("Rows      : ",data.shape[0])
print ("Columns   : ",data.shape[1])
print ("\nFeatures : \n",data.columns.tolist())
print ("\nMissing values : ", data.isnull().sum().values.sum())
print ("\nUnique values : \n",data.nunique())
```

```
Rows      : 376703
Columns   : 24
```

Features :

['date\_time', 'site\_name', 'posa\_continent', 'user\_location\_country', 'user\_location\_region',

Missing values : 136337

Unique values :

date_time	375047
site_name	42
posa_continent	5
user_location_country	213
user_location_region	871
user_location_city	18645
orig_destination_distance	223465
user_id	262797
is_mobile	2
is_package	2
channel	11
srch_ci	1105
srch_co	1106
srch_adults_cnt	10
srch_children_cnt	10
srch_rm_cnt	9
srch_destination_id	15938
srch_destination_type_id	9
is_booking	2
cnt	37
hotel_continent	7
hotel_country	197
hotel_market	2045
hotel_cluster	100
dtype: int64	

CPU times: user 1.89 s, sys: 1.82 s, total: 3.71 s

Wall time: 4.35 s

In [175]: *##missing value percentage*

```
percent_missing = data.isnull().sum() * 100 / len(data)
missing_value_df = pd.DataFrame({'column_name': data.columns,
                                'percent_missing': percent_missing})
missing_value_df
```

Out[175]:

	column_name	percent_missing
date_time	date_time	0.000000
site_name	site_name	0.000000
posa_continent	posa_continent	0.000000
user_location_country	user_location_country	0.000000
user_location_region	user_location_region	0.000000

user_location_city	user_location_city	0.000000
orig_destination_distance	orig_destination_distance	35.933613
user_id	user_id	0.000000
is_mobile	is_mobile	0.000000
is_package	is_package	0.000000
channel	channel	0.000000
srch_ci	srch_ci	0.129280
srch_co	srch_co	0.129280
srch_adults_cnt	srch_adults_cnt	0.000000
srch_children_cnt	srch_children_cnt	0.000000
srch_rm_cnt	srch_rm_cnt	0.000000
srch_destination_id	srch_destination_id	0.000000
srch_destination_type_id	srch_destination_type_id	0.000000
is_booking	is_booking	0.000000
cnt	cnt	0.000000
hotel_continent	hotel_continent	0.000000
hotel_country	hotel_country	0.000000
hotel_market	hotel_market	0.000000
hotel_cluster	hotel_cluster	0.000000

In [41]: data.describe()

Out [41]:

	site_name	posa_continent	user_location_country \
count	376703.000000	376703.000000	376703.000000
mean	9.811220	2.679803	86.197123
std	11.985748	0.748484	59.239274
min	2.000000	0.000000	0.000000
25%	2.000000	3.000000	66.000000
50%	2.000000	3.000000	66.000000
75%	15.000000	3.000000	71.000000
max	53.000000	4.000000	239.000000

	user_location_region	user_location_city	orig_destination_distance \
count	376703.000000	376703.000000	241340.000000
mean	308.132784	27793.453418	1970.497121
std	208.878863	16762.012048	2233.786783
min	0.000000	0.000000	0.005600
25%	174.000000	13087.000000	312.906825
50%	312.000000	27655.000000	1137.305950
75%	385.000000	42396.000000	2553.017375
max	1027.000000	56507.000000	12052.021000

	user_id	is_mobile	is_package	channel ... \
count	3.767030e+05	376703.000000	376703.000000	376703.000000 ...
mean	6.044845e+05	0.135207	0.248278	5.868459 ...
std	3.508230e+05	0.341945	0.432014	3.717852 ...
min	3.000000e+00	0.000000	0.000000	0.000000 ...
25%	2.983800e+05	0.000000	0.000000	2.000000 ...

50%	6.042430e+05	0.000000	0.000000	9.000000	...
75%	9.109655e+05	0.000000	0.000000	9.000000	...
max	1.198783e+06	1.000000	1.000000	10.000000	...

	srch_children_cnt	srch_rm_cnt	srch_destination_id	\
count	376703.000000	376703.000000	376703.000000	
mean	0.331980	1.112752	14440.410429	
std	0.729092	0.458563	11075.148990	
min	0.000000	0.000000	4.000000	
25%	0.000000	1.000000	8267.000000	
50%	0.000000	1.000000	9147.000000	
75%	0.000000	1.000000	18790.000000	
max	9.000000	8.000000	65068.000000	

	srch_destination_type_id	is_booking	cnt	\
count	376703.000000	376703.000000	376703.000000	
mean	2.580457	0.078972	1.482130	
std	2.151231	0.269695	1.199764	
min	1.000000	0.000000	1.000000	
25%	1.000000	0.000000	1.000000	
50%	1.000000	0.000000	1.000000	
75%	5.000000	0.000000	2.000000	
max	9.000000	1.000000	49.000000	

	hotel_continent	hotel_country	hotel_market	hotel_cluster
count	376703.000000	376703.000000	376703.000000	376703.000000
mean	3.155796	81.296385	600.239868	49.832327
std	1.622880	56.169040	511.170282	28.928797
min	0.000000	0.000000	0.000000	0.000000
25%	2.000000	50.000000	160.000000	25.000000
50%	2.000000	50.000000	597.000000	49.000000
75%	4.000000	106.000000	701.000000	73.000000
max	6.000000	212.000000	2117.000000	99.000000

[8 rows x 21 columns]

In [42]: *#to check data types*  
data.dtypes

```
Out[42]: date_time      object
site_name      int64
posa_continent  int64
user_location_country  int64
user_location_region  int64
user_location_city    int64
orig_destination_distance  float64
user_id            int64
is_mobile          int64
```

```

is_package          int64
channel             int64
srch_ci             object
srch_co             object
srch_adults_cnt     int64
srch_children_cnt   int64
srch_rm_cnt         int64
srch_destination_id int64
srch_destination_type_id int64
is_booking          int64
cnt                 int64
hotel_continent     int64
hotel_country       int64
hotel_market        int64
hotel_cluster       int64
dtype: object

```

## 2.2 1.2.Data Manipulation

In [176]: *#change data types*

```

columns = data.columns.tolist()
datetime_var = ['date_time', 'srch_ci', 'srch_co']

numeric_var = ['orig_destination_distance', 'is_mobile', 'is_package', 'srch_adults_cnt',
               'is_booking', 'cnt']

cat_var = [i for i in columns if (i not in datetime_var and i not in numeric_var)]

```

In [177]: *def change\_datatype():*

```

    for i in datetime_var:
        data[i] = data[i].astype('datetime64[ns]')
    return data

```

```

data = change_datatype()

```

In [45]: *#check data types*

```

data.dtypes

```

```

Out[45]: date_time          datetime64[ns]
site_name                  int64
posa_continent             int64
user_location_country      int64
user_location_region       int64
user_location_city         int64
orig_destination_distance  float64
user_id                    int64
is_mobile                  int64
is_package                 int64
channel                    int64

```

```

srch_ci                datetime64[ns]
srch_co                datetime64[ns]
srch_adults_cnt        int64
srch_children_cnt      int64
srch_rm_cnt            int64
srch_destination_id    int64
srch_destination_type_id int64
is_booking             int64
cnt                   int64
hotel_continent        int64
hotel_country          int64
hotel_market           int64
hotel_cluster          int64
dtype: object

```

## 3 2.Exploratory Data Analysis

### 3.1 2.1.Hotel Cluster Distribution

```

In [45]: #define a function to plot interactive distrbution graph
def distribution_plot(dataset,column,title,xtitle,ytitle):
    trace = go.Histogram(x=dataset[column], opacity=0.7, marker={"line": {"color": "#
    layout = go.Layout(title=title, xaxis={"title": xtitle, "showgrid": False},
                        yaxis={"title": ytitle, "showgrid": False},plot_bgcolor='rgba(
                        paper_bgcolor='rgba(0,0,0,0)') #showgrid:False to remove gridli
    figure = {"data": [trace], "layout": layout}

    py.iplot(figure)

In [46]: distribution_plot(data,'hotel_cluster',f"Hotel Cluster Distribution","Hotel Cluster",

In [48]: #hotel cluster counts
data['hotel_cluster'].value_counts()

Out[48]: 91      10363
         41      7792
         48      7449
         64      7063
         65      6778
         ...
         35      1359
         53      1353
         88      1098
         27      1044
         74       508
Name: hotel_cluster, Length: 100, dtype: int64

```



## 3.2 2.2.Other Attrition Distribution

```
In [55]: plot_data = data.copy()
plot_data['is_mobile'] = plot_data["is_mobile"].replace({1:"Yes",0:"No"})
plot_data['is_package'] = plot_data["is_package"].replace({1:"Yes",0:"No"})
plot_data['is_booking'] = plot_data["is_booking"].replace({1:"Yes",0:"No"})
book = plot_data[plot_data['is_booking']=="Yes"]
notbook = plot_data[plot_data['is_booking']=="No"]

In [52]: #define a function to plot distribution by booking decision
def histogram(column) :
    trace1 = go.Histogram(x = book[column],
                           histnorm= "percent",
                           name = "Booked",
                           marker = dict(line = dict(width = .5,
                                                         color = "black"
                                                         ),
                                         ),
                           opacity = .9
                           )

    trace2 = go.Histogram(x = notbook[column],
                           histnorm = "percent",
                           name = "Not Booked",
                           marker = dict(line = dict(width = .5,
                                                         color = "black"
                                                         ),
                                         ),
                           opacity = .9
                           )

    data = [trace1,trace2]
    layout = go.Layout(dict(title =column + " distribution in booking attrition ",
                             plot_bgcolor = "rgb(243,243,243)",
                             paper_bgcolor = "rgb(243,243,243)",
                             xaxis = dict(gridcolor = 'rgb(255, 255, 255)',
                                           title = column,
                                           zerolinewidth=1,
                                           ticklen=5,
                                           gridwidth=2
                                           ),
                             yaxis = dict(gridcolor = 'rgb(255, 255, 255)',
                                           title = "percent",
                                           zerolinewidth=1,
                                           ticklen=5,
                                           gridwidth=2
                                           ),
                             )
    )
```

```
fig = go.Figure(data=data,layout=layout)

py.iplot(fig)
```

```
In [57]: col = ['orig_destination_distance', 'is_mobile', 'is_package', 'channel', 'srch_adults_cnt',
               'srch_rm_cnt', 'srch_destination_type_id', 'hotel_continent']
for i in col:
    histogram(i)
```

## 4 3. Data processing

### 4.1 3.1. Filling Missing Value

```
In [178]: #check number of rows that have missing values
dis_na = data['orig_destination_distance'].isnull().values.ravel().sum()
print(dis_na)
```

135363

```
In [179]: def filled_distance():
    dis_na = data['orig_destination_distance'].isnull().values.ravel().sum()
    #first step fill by the user location city and srch destination id group
    #filled about 4k record, 131808 NA left
    data['orig_destination_distance'] = data.groupby(['user_location_city', 'srch_destination_type_id']).apply(
        lambda x: x.fillna(np.mean(x)))
    dis_na1 = data['orig_destination_distance'].isnull().values.ravel().sum()
    print('Filled {} records and there are {} NA records left'.format(dis_na-dis_na1))
    #second step fill by the user location country and hotel country group
    #filled 64651 records and 67157 left
    data['orig_destination_distance'] = data.groupby(['user_location_city', 'hotel_continent']).apply(
        lambda x: x.fillna(np.mean(x)))
    dis_na2 = data['orig_destination_distance'].isnull().values.ravel().sum()
    print('Filled {} records and there are {} NA records left'.format(dis_na1-dis_na2))
    #third step fill by the user location country and search destination type id group
    #filled 32507 records and 34650 left
    data['orig_destination_distance'] = data.groupby(['user_location_country', 'srch_destination_type_id']).apply(
        lambda x: x.fillna(np.mean(x)))
    dis_na3 = data['orig_destination_distance'].isnull().values.ravel().sum()
    print('Filled {} records and there are {} NA records left'.format(dis_na2-dis_na3))
    #forth step fill by the posa continent group
    #filled all the missing value
    data['orig_destination_distance'] = data.groupby(['posa_continent']).apply(
        lambda x: x.fillna(np.mean(x)))
    dis_na4 = data['orig_destination_distance'].isnull().values.ravel().sum()
    print('Filled {} records and there are {} NA records left'.format(dis_na3-dis_na4))
    return data
```

```
In [180]: filled_distance()
```

```
Filled 3555 records and there are 131808 NA records left
Filled 9541 records and there are 122267 NA records left
Filled 82791 records and there are 39476 NA records left
Filled 39476 records and there are 0 NA records left
```

```
Out[180]:
```

	date_time	site_name	posa_continent	\
14135162	2014-01-26 14:49:27	11	3	
18984109	2014-01-13 19:33:04	22	2	
26309215	2013-06-03 21:47:36	2	3	
6926715	2014-01-02 16:11:51	13	1	
21882923	2014-09-30 10:29:23	37	1	
...	...	...	...	
8251929	2014-09-23 19:55:38	2	3	
32607965	2014-12-31 14:00:53	37	1	
30217917	2014-08-06 08:08:43	2	3	
29750021	2014-02-18 13:31:30	10	0	
549466	2013-03-28 03:08:19	2	3	

	user_location_country	user_location_region	user_location_city	\
14135162	168	45	7182	
18984109	0	147	10568	
26309215	66	184	11878	
6926715	46	171	19639	
21882923	69	573	33444	
...	...	...	...	
8251929	194	38	42328	
32607965	69	926	53290	
30217917	66	220	2086	
29750021	182	416	32100	
549466	66	348	48862	

	orig_destination_distance	user_id	is_mobile	is_package	...	\
14135162	1862.949101	178107	0	0	...	
18984109	2854.719471	1024412	0	0	...	
26309215	648.255400	216672	0	0	...	
6926715	5566.765700	1179327	0	0	...	
21882923	3419.160513	128601	0	0	...	
...	...	...	...	...	...	
8251929	1862.949101	118510	0	0	...	
32607965	3419.160513	302897	0	0	...	
30217917	528.022400	1184505	1	1	...	
29750021	5041.088800	1185797	0	0	...	
549466	209.120700	667832	0	0	...	

	srch_children_cnt	srch_rm_cnt	srch_destination_id	\
--	-------------------	-------------	---------------------	---

14135162	0	1	33648
18984109	0	1	468
26309215	2	1	26663
6926715	0	1	22890
21882923	0	1	23479
...	...	...	...
8251929	0	1	8242
32607965	0	1	25967
30217917	1	1	1152
29750021	0	1	8218
549466	0	1	8291

	srch_destination_type_id	is_booking	cnt	hotel_continent	\
14135162	1	1	1	5	
18984109	1	0	1	3	
26309215	1	0	4	2	
6926715	5	0	1	3	
21882923	6	0	5	6	
...	...	...	...	...	
8251929	1	0	1	3	
32607965	6	0	1	6	
30217917	1	0	1	4	
29750021	1	0	2	2	
549466	1	0	1	2	

	hotel_country	hotel_market	hotel_cluster
14135162	194	1555	76
18984109	48	153	9
26309215	50	707	15
6926715	182	46	57
21882923	70	19	21
...	...	...	...
8251929	171	61	37
32607965	70	134	18
30217917	47	1502	65
29750021	50	743	70
549466	50	191	91

[376703 rows x 24 columns]

```
In [ ]: print('duration: ',pd.datetime.now() - start_time)
```

## 4.2 3.2. Target Encoding

```
In [49]: target = ['hotel_cluster']
userid = ['user_id']
cat_var = [i for i in cat_var if i not in target]+userid
print(target)
```

```

        print(cat_var)

['hotel_cluster']
['site_name', 'posa_continent', 'user_location_country', 'user_location_region', 'user_location']

```

```

In [50]: #train test split
from sklearn.model_selection import train_test_split
train,test = train_test_split(data,test_size =.25 ,random_state = 111)
cols      = [i for i in data.columns if i not in target]
train_X = train[cols]
train_Y = train[target]
test_X  = test[cols]
test_Y  = test[target]
train1 = train.copy()

In [18]: def target_encoder(df,df_toencoded, column, target, method='mean'):
    if method == 'mean':
        df1 = df.groupby(column)[target].mean().reset_index()
    elif method == 'median':
        df1 = df.groupby(column)[target].median().reset_index()
    elif method == 'std':
        df1 = df.groupby(column)[target].std().reset_index()
    elif method == 'mode':
        df1 = df.groupby(column)[target].apply(pd.Series.mode).reset_index()
    else:
        raise ValueError("Incorrect method supplied: '{}'. Must be one of 'mean', 'median', 'std', 'mode'")

    encode_dict = {k:v for k, v in zip(df1[column],df1[target])}
    encoded_column = [encode_dict[k] for k in df_toencoded[column]]

    return encoded_column

encode_col = ['hotel_country']

#for i in encode_col:
#    train[i] = target_encoder(train1,train,i,'hotel_cluster','mode')

#train.head()

```

```

Out[18]:
      date_time  site_name  posa_continent  \
34608371 2014-05-23 09:42:03           2      3
33215220 2014-08-24 10:52:53          24      2
31322656 2013-12-26 19:15:58          34      3
9852244  2014-06-12 01:38:38           2      3
3315432  2014-08-09 08:03:05          11      3

      user_location_country  user_location_region  user_location_city  \
34608371                  66                  348                48862

```

33215220	3	70	32441
31322656	205	354	16084
9852244	66	462	46651
3315432	205	354	49492

	orig_destination_distance	user_id	is_mobile	is_package	...	\
34608371	3831.303900	666517	0	0	...	
33215220	7363.881774	929132	0	0	...	
31322656	2096.279100	457168	0	0	...	
9852244	861.480200	752047	0	0	...	
3315432	6131.312300	206212	0	1	...	

	srch_children_cnt	srch_rm_cnt	srch_destination_id	\
34608371	0	1	8788	
33215220	0	1	8785	
31322656	0	1	8288	
9852244	0	1	8250	
3315432	0	1	8863	

	srch_destination_type_id	is_booking	cnt	hotel_continent	\
34608371	1	0	1	6	
33215220	1	0	1	6	
31322656	1	0	1	2	
9852244	1	0	1	2	
3315432	1	0	1	0	

	hotel_country	hotel_market	hotel_cluster
34608371	82	1880	46
33215220	8	35	58
31322656	55	399	95
9852244	91	628	45
3315432	92	59	78

[5 rows x 24 columns]

### 4.3 3.3. Ref Variable Creation

```
In [161]: ##previous hotel cluster
```

```
train_user = set(train.user_id)
test_user = set(test.user_id)
new_user = test_user - train_user
new_user = list(new_user)
```

```
In [52]: train['rec_hotel_cluster'] = train.groupby(['user_id'])['hotel_cluster'].transform(
        lambda x:pd.Series.mode(x)[0])
```

```
In [ ]: #for existing user, match rec_hotel_cluster
        #for new_user, find similar user
```

```
In [56]: data[data['user_id'].isin(train_user)]
```

```
Out [56]:
```

	date_time	site_name	posa_continent	\
14135162	2014-01-26 14:49:27	11	3	
18984109	2014-01-13 19:33:04	22	2	
26309215	2013-06-03 21:47:36	2	3	
6926715	2014-01-02 16:11:51	13	1	
21882923	2014-09-30 10:29:23	37	1	
...	...	...	...	
34757536	2013-01-25 00:22:37	24	2	
8251929	2014-09-23 19:55:38	2	3	
32607965	2014-12-31 14:00:53	37	1	
29750021	2014-02-18 13:31:30	10	0	
549466	2013-03-28 03:08:19	2	3	

	user_location_country	user_location_region	user_location_city	\
14135162	168	45	7182	
18984109	0	147	10568	
26309215	66	184	11878	
6926715	46	171	19639	
21882923	69	573	33444	
...	...	...	...	
34757536	3	48	48781	
8251929	194	38	42328	
32607965	69	926	53290	
29750021	182	416	32100	
549466	66	348	48862	

	orig_destination_distance	user_id	is_mobile	is_package	...	\
14135162	1877.175685	178107	0	0	...	
18984109	2854.719471	1024412	0	0	...	
26309215	648.255400	216672	0	0	...	
6926715	5566.765700	1179327	0	0	...	
21882923	2083.922543	128601	0	0	...	
...	...	...	...	...	...	
34757536	8300.060200	12803	0	0	...	
8251929	1877.175685	118510	0	0	...	
32607965	2083.922543	302897	0	0	...	
29750021	5041.088800	1185797	0	0	...	
549466	209.120700	667832	0	0	...	

	srch_children_cnt	srch_rm_cnt	srch_destination_id	\
14135162	0	1	33648	
18984109	0	1	468	
26309215	2	1	26663	
6926715	0	1	22890	
21882923	0	1	23479	
...	...	...	...	

34757536	0	1	8253
8251929	0	1	8242
32607965	0	1	25967
29750021	0	1	8218
549466	0	1	8291

	srch_destination_type_id	is_booking	cnt	hotel_continent	\
14135162	1	1	1	5	
18984109	1	0	1	3	
26309215	1	0	4	2	
6926715	5	0	1	3	
21882923	6	0	5	6	
...	...	...	...	...	
34757536	1	0	1	6	
8251929	1	0	1	3	
32607965	6	0	1	6	
29750021	1	0	2	2	
549466	1	0	1	2	

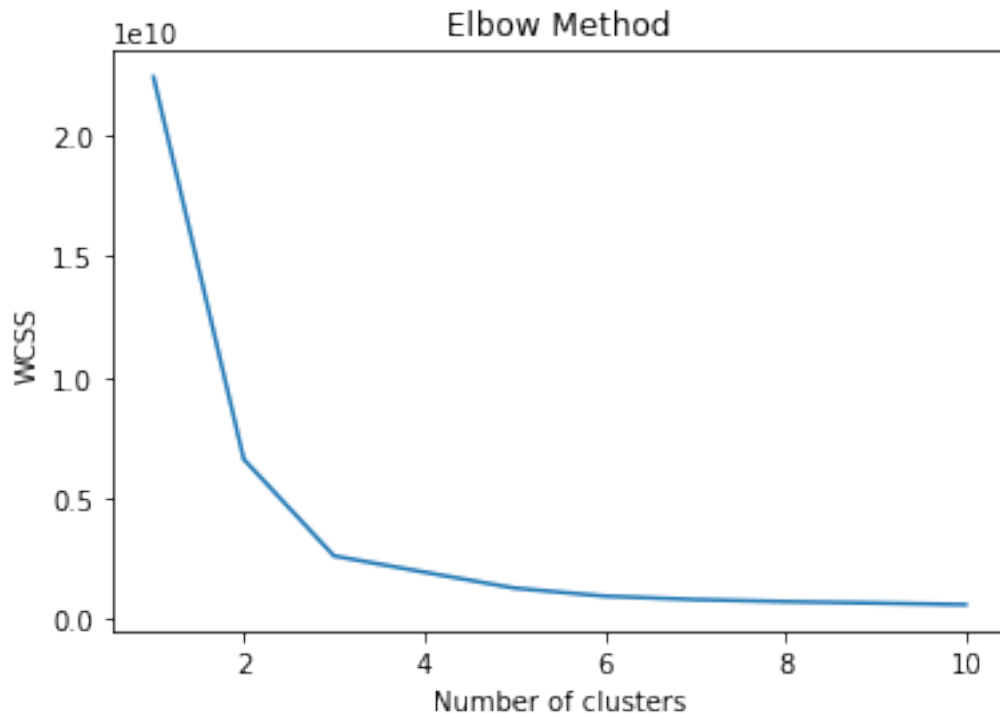
	hotel_country	hotel_market	hotel_cluster
14135162	194	1555	76
18984109	48	153	9
26309215	50	707	15
6926715	182	46	57
21882923	70	19	21
...	...	...	...
34757536	70	19	25
8251929	171	61	37
32607965	70	134	18
29750021	50	743	70
549466	50	191	91

[322406 rows x 24 columns]

```
In [136]: #get unique user_id record and plot kmeans elbow plot to find optimal number of clusters
test['earliest'] = test.groupby(['user_id'])['date_time'].transform(
    lambda x:x.min())
test_df = test[test['date_time']==test['earliest']]
from sklearn.datasets.samples_generator import make_blobs
from sklearn.cluster import KMeans
X_df = test_df[['site_name', 'user_location_country', 'hotel_country', 'hotel_market', 'hotel_cluster']]
X_df = X_df.set_index('user_id')
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=None)
    kmeans.fit(X_df)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
```



```
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



```
In [137]: kmeans = KMeans(n_clusters=3, init='k-means++', max_iter=300, n_init=10, random_state=42)
pred_y = kmeans.fit_predict(X_df)
X_df['cluster'] = pred_y
X_df = X_df.reset_index()
cluster_0 = list(set(X_df[X_df['cluster']==0]['user_id']))
cluster_1 = list(set(X_df[X_df['cluster']==1]['user_id']))
cluster_2 = list(set(X_df[X_df['cluster']==2]['user_id']))
```

```
In [154]: def rec_cluster():
    #find existing user then match the rec_hotel_cluster value based on the train data
    cluster_dict = {k:v for k,v in zip(train['user_id'],train['rec_hotel_cluster'])}
    df_old = test[test['user_id'].isin(train_user)]
    df_new = test[~test['user_id'].isin(train_user)]
    col_old = [cluster_dict[k] for k in df_old['user_id']]
    df_old['rec_hotel_cluster'] = col_old
    #for new user, find mode in similar cluster
    df_new0 = df_new[df_new['user_id'].isin(cluster_0)]
    df_new0['rec_hotel_cluster'] = df_new0['hotel_cluster'].mode()[0]
    df_new1 = df_new[df_new['user_id'].isin(cluster_1)]
```

```

df_new1['rec_hotel_cluster'] = df_new1['hotel_cluster'].mode()[0]
df_new2 = df_new[df_new['user_id'].isin(cluster_2)]
df_new2['rec_hotel_cluster'] = df_new2['hotel_cluster'].mode()[0]
frames = [train,df_old, df_new0, df_new1,df_new2]
result = pd.concat(frames)
return result

```

```

In [152]: df_new = test[~test['user_id'].isin(train_user)]
df_new0 = df_new[df_new['user_id'].isin(cluster_0)]

```

```

In [153]: df_new0

```

```

Out[153]:

```

	date_time	site_name	posa_continent	\
15467234	2014-06-07 07:29:22	2	3	
19922510	2014-10-04 05:43:36	34	3	
11981320	2014-10-22 18:50:19	10	0	
7854674	2014-11-18 11:37:10	2	3	
35772501	2014-08-28 18:47:32	2	3	
...	...	...	...	
903321	2014-11-19 18:00:38	2	3	
14840496	2014-09-22 18:58:08	2	3	
18889807	2014-12-28 13:02:59	2	3	
20923988	2013-04-28 20:58:26	34	3	
446714	2014-09-16 08:53:21	2	3	

	user_location_country	user_location_region	user_location_city	\
15467234	80	38	52486	
19922510	205	354	21728	
11981320	182	376	14405	
7854674	66	351	52368	
35772501	66	442	23258	
...	...	...	...	
903321	66	337	3591	
14840496	66	260	22666	
18889807	66	318	51298	
20923988	205	155	14703	
446714	66	331	2639	

	orig_destination_distance	user_id	is_mobile	is_package	...	\
15467234	1877.175685	299996	0	0	...	
19922510	298.178700	420	0	0	...	
11981320	4106.045000	380410	0	0	...	
7854674	881.810500	163201	0	0	...	
35772501	1233.609700	177098	0	0	...	
...	...	...	...	...	...	
903321	62.753600	590085	1	0	...	
14840496	103.351700	1015569	0	0	...	
18889807	249.053800	751293	1	0	...	

20923988	2427.830200	544688	0	0	...
446714	144.724700	367278	0	0	...

	srch_rm_cnt	srch_destination_id	srch_destination_type_id	\
15467234	1	8230	1	
19922510	1	108	1	
11981320	1	8260	1	
7854674	1	13436	4	
35772501	1	27140	6	
...	...	...	...	
903321	1	11569	1	
14840496	2	12014	1	
18889807	1	8230	1	
20923988	1	8267	1	
446714	2	8274	1	

	is_booking	cnt	hotel_continent	hotel_country	hotel_market	\
15467234	0	1	2	50	637	
19922510	0	1	2	50	829	
11981320	0	1	2	50	701	
7854674	0	1	2	50	682	
35772501	0	1	2	50	637	
...	...	...	...	...	...	
903321	0	3	2	50	623	
14840496	0	2	2	50	644	
18889807	0	1	2	50	637	
20923988	0	1	2	50	675	
446714	0	1	2	50	684	

	hotel_cluster	earlist
15467234	69	2014-06-07 07:29:22
19922510	13	2014-10-04 05:43:36
11981320	18	2014-10-22 18:50:19
7854674	31	2014-11-18 11:37:10
35772501	91	2014-08-28 18:47:32
...	...	...
903321	79	2014-11-19 18:00:38
14840496	55	2014-09-22 18:58:08
18889807	91	2014-12-28 13:02:59
20923988	98	2013-04-28 20:58:26
446714	28	2014-09-16 08:53:21

[19895 rows x 25 columns]

```
In [166]: data = rec_cluster()
          data = data.drop(['earlist'], axis=1)
```

```
In [167]: data.to_csv ('data.csv')
```

```
In [ ]: print('duration: ',pd.datetime.now() - start_time)
```