PROBLEM STATEMENT-

XRides data-set includes data for ~40,000 trips. The data-set records major elements of a trip such as the location it was booked, the time it was booked, chosen package for the trip and other features. We need to analyze this data set so that we can increase business, make life of cab-drivers more efficient and also reduce cancellation of rides.

SOLUTION-

1. The basic approach was to analyze the data and find locations that have highest trip booking volumes. We had 3 features that can help us identify these locations - from_area_id, from_lat and from_long. We identified that there are 598 from_area_id and XRides gains 19.07% of it's business from the area id's (393.0, 572.0 and 293.0). If XRides focuses on these three regions it can gain more business. On analyzing these 3 areas we can develope a personalized strategy for them. Further, there are heatmaps that show how time and days play an important role in cab bookings in these particular area and these heatmap would help in identifying the time domain for particular weekdays to increase business.

2. We identified that many cabs were cancelled from_area_id (393.0 and 572.0, cancellations above 100) these cancellation may have been caused due to locality problems or the duration of the cab to reach the location during traffic hours. These location could use increased number of cabs at peak hours. There are dataframes which show the trends of cab cancellation on the basis of time, different areas and weekdays.

The detailed answer is at the bottom of the page

Initial EDA

In [1]:
```
#importing python libraries for analysis.
import numpy as np
import pandas as pd
```

In [2]:
```
#importing libraries essential for plotting of data on graphs
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [3]:
```
#importing data
df = pd.read_csv('Data.csv')
```

In [4]:
```
df.head(3)
```

Out[4]:

	id	user_id	vehicle_model_id	package_id	travel_type_id	from_area_id	to_area_id	from_city_id	to_city
0	132512	22177	28	NaN	2	83.0	448.0	NaN	NaN
1	132513	21413	12	NaN	2	1010.0	540.0	NaN	NaN
2	132514	22178	12	NaN	2	1301.0	1034.0	NaN	NaN

In [5]:
```
#to check for total, missing values and data types.
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 43431 entries, 0 to 43430
Data columns (total 19 columns):
id                     43431 non-null int64
user_id                43431 non-null int64
vehicle_model_id       43431 non-null int64
package_id             7550 non-null float64
travel_type_id         43431 non-null int64
from_area_id           43343 non-null float64
to_area_id             34293 non-null float64
from_city_id           16345 non-null float64
to_city_id             1588 non-null float64
from_date              43431 non-null object
to_date                25541 non-null object
online_booking         43431 non-null int64
mobile_site_booking    43431 non-null int64
booking_created        43431 non-null object
from_lat               43338 non-null float64
from_long              43338 non-null float64
to_lat                 34293 non-null float64
to_long                34293 non-null float64
Car_Cancellation       43431 non-null int64
dtypes: float64(9), int64(7), object(3)
memory usage: 6.3+ MB
```

In [6]:
```
df.from_area_id.nunique()
```

Out[6]: 598

Some features like package_id, from_city_id, to_city_id, to_date and many other features (see result above) have missing values and hence not reliable for analysis.

CONVERTING DATE

In [7]:
```
#Dividing date-time to DAY of MONTH - WEEKDAY - HOUR into seperate columns
df['from_date']=df['from_date'].map(pd.to_datetime)
```

In [8]:
```
def get_dom(dt):
    return dt.day
df['dayofm']=df['from_date'].map(get_dom)
```

In [9]:
```
def get_weekday(dt):
    return dt.weekday()

df['weekday'] = df['from_date'].map(get_weekday)
```

In [10]:
```
def get_hour(dt):
    return dt.hour
df['hour']=df['from_date'].map(get_hour)
```

In [11]:
```
df.head(3)
```

Out[11]:

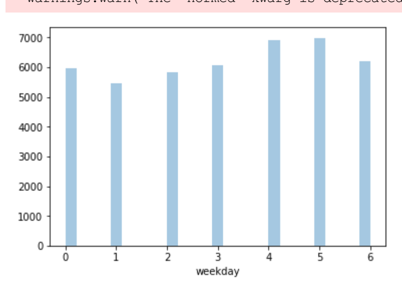
	id	user_id	vehicle_model_id	package_id	travel_type_id	from_area_id	to_area_id	from_city_id	to_city
0	132512	22177	28	NaN	2	83.0	448.0	NaN	NaN
1	132513	21413	12	NaN	2	1010.0	540.0	NaN	NaN
2	132514	22178	12	NaN	2	1301.0	1034.0	NaN	NaN

3 rows × 22 columns

CHECKING TRAFFIC BY DAY

In [12]:
```
#Rides Taken by day
sns.distplot(df['weekday'],kde=False);
```

```
C:\Users\Sushant\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarning: The 'no
rmed' kwarg is deprecated, and has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



From the above graph we get to know that most cabs are booked on weekends, i.e., FRIDAYs and SATURDAYs

COMPARING PARTICULAR FROM_AREA_ID's TIME AND DAY

In [214]:
```
#Checking most cabs booked in particular area
df_area.head()
```

Out[214]:
```
393.0     3858
571.0     1631
293.0     1052
585.0      911
1010.0     768
Name: from_area_id, dtype: int64
```

In [216]:
```
# percentage of trips of major three areas
((3858+1631+1052)/34293) * 100
```

Out[216]: 19.073863470679147

In [218]:
```
# percentage of trips of major area (individual)
(3858/34293) * 100
```

Out[218]: 11.25010935176275

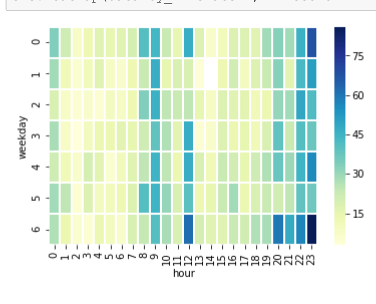
In [222]:
```
# percentage of trips of major area (individual)
(1631/34293) * 100
```

Out[222]: 4.756072667891406

In [221]:
```
# percentage of trips of major area (individual)
(1052/34293) * 100
```

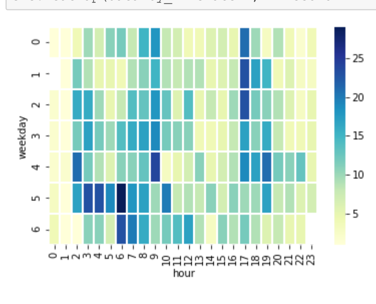
Out[221]: 3.0676814510249906

In [207]:
```
#Plotting a heatmap to check cabs booked on a particular day at which time and in a PARTICULAR AREA-
393.0
df11 = df.loc[df['from_area_id'] == 393.0]

def count_rows(rows):
    return len(rows)

by_date11 = df11.groupby('dayofm').apply(count_rows)

by_TimeDate11 = df11.groupby('weekday hour'.split()).apply(count_rows).unstack()

sns.heatmap(data=by_TimeDate11, linecolor='white',linewidths=1, cmap='YlGnBu');
```



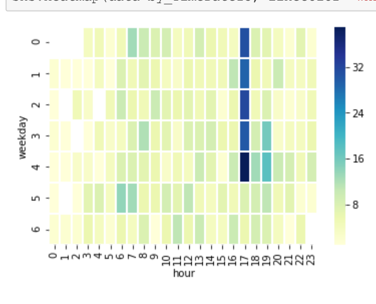
We can make out from the heatmap that most cabs in the area_id 393.0 are booked at 23:00 and during office commute hours.

In [208]:
```
#Plotting a heatmap to check cabs booked on a particular day at which time and in a PARTICULAR AREA-
571.0
df12 = df.loc[df['from_area_id'] == 571.0]

def count_rows(rows):
    return len(rows)

by_date12 = df12.groupby('dayofm').apply(count_rows)

by_TimeDate12 = df12.groupby('weekday hour'.split()).apply(count_rows).unstack()

sns.heatmap(data=by_TimeDate12, linecolor='white',linewidths=1, cmap='YlGnBu');
```



We can make out of the heatmap that most cabs in the area_id 571.0 are booked at 6:00 and during office commute hours.

In [204]:
```
#Plotting a heatmap to check cabs booked on a particular day at which time and in a PARTICULAR AREA-
293.0
df13 = df.loc[df['from_area_id'] == 293.0]

def count_rows(rows):
    return len(rows)

by_date13 = df13.groupby('dayofm').apply(count_rows)

by_TimeDate13 = df13.groupby('weekday hour'.split()).apply(count_rows).unstack()

by_TimeDate13

sns.heatmap(data=by_TimeDate13, linecolor='white',linewidths=1, cmap='YlGnBu');
```

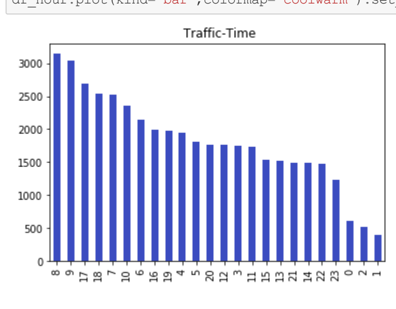


We can make out of the heatmap that most cabs in the area_id 293.0 are booked during office commute hours.

CHECKING TRAFFIC BY HOUR

In [13]:
```
#Rides Taken by hour
df_hour= df.hour.value_counts()
```

In [14]:
```
df_hour.plot(kind='bar',colormap='coolwarm').set_title(' Traffic-Time');
```



The graph above clearly shows that most rides are taken during the office hours i.e., between 8:00-9:59 and during the evening between 17:00-18:59

CHECKING TRAFFIC BY DAY AND HOUR

In [177]:
```
def count_rows(rows):
    return len(rows)

by_date = df.groupby('dayofm').apply(count_rows)
```

In [178]:
```
by_TimeDate = df.groupby('weekday hour'.split()).apply(count_rows).unstack()
```

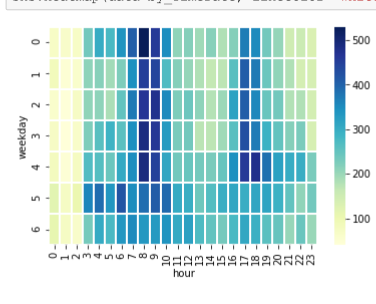
In [179]:
```
by_TimeDate
```

Out[179]:

hour	0	1	2	3	4	5	6	7	8	9	...	14	15	16	17	18	19	20	21	22	23
weekday																					
0	71	64	70	237	301	276	342	407	530	460	...	217	184	220	371	353	237	207	151	156	133
1	85	50	61	212	217	194	226	346	452	444	...	166	172	262	409	375	244	211	183	143	139
2	61	44	73	211	212	187	253	374	466	476	...	180	200	318	406	358	247	236	181	184	146
3	73	41	67	226	262	290	259	347	489	464	...	172	196	262	430	373	293	253	219	230	140
4	82	48	76	270	265	245	308	350	490	448	...	230	248	345	461	478	385	321	301	300	230
5	120	74	105	359	390	337	420	352	387	411	...	268	297	312	300	314	315	293	253	211	237
6	112	74	64	233	305	277	336	353	334	332	...	253	234	278	309	296	259	249	205	246	203

7 rows × 24 columns

In [18]:
```
#plotting a heatmap to see when and at which day there's more traffic compared to others
sns.heatmap(data=by_TimeDate, linecolor='white',linewidths=1, cmap='YlGnBu');
```



The above heatmap basically depicts the number of cabs that are booked on each day and on which time. Through this graph we infer that most cabs are booked during the office commute hours, except on Saturdays and Sundays.

CHECKING TRAFFIC BY LONG AND LAT

In [59]:
```
#Checking unique values in from_lat and from_long.
df[['from_lat', 'from_long']].nunique()
```

Out[59]:
```
from_lat     466
from_long    462
dtype: int64
```

In [62]:
```
#Creating a dummy table with latitude, longitude and a Unique id.
a = pd.DataFrame(df.groupby(['from_lat', 'from_long'])['id'].count())
```

In [63]:
```
# combine lat and long (from) to get the specific location of the place
df['from_lat_long'] = df['from_lat'].astype(str)+","+df['from_long'].astype(str)
```

CREATING DUMMY LOCATION AND PROVIDING THEM A NAME

In [64]:
```
# adding a name to each location
dummy_location = []
for i in range(0,467):
    x = 'Loc'+'-'+str(i)
    dummy_location.append(x)
```

In [23]:
```
#df_final = pd.merge(df, df1)
b = a.reset_index()
df1 = b[['from_lat', 'from_long']]
df1['dummy_loc'] = pd.Series(dummy_location).values
```

In [24]:
```
df1.head()
```

Out[24]:

	from_lat	from_long	dummy_loc
0	12.77663	77.56382	Loc-0
1	12.78091	77.77131	Loc-1
2	12.78665	77.63761	Loc-2
3	12.79665	77.38693	Loc-3
4	12.80257	77.70453	Loc-4

In [25]:
```
#get the location on the original dataset
df_final = pd.merge(df, df1, on = ['from_lat', 'from_long'], how = 'left')
```

In [67]:
```
#to check now, which columns exist in the dataframe
colnames = df_final.columns
```

In [103]:
```
#to check now, which columns exist in the dataframe
colnames
```

Out[103]:
```
Index(['id', 'user_id', 'vehicle_model_id', 'package_id', 'travel_type_id',
       'from_area_id', 'to_area_id', 'from_city_id', 'to_city_id', 'from_date',
       'to_date', 'online_booking', 'mobile_site_booking', 'booking_created',
       'from_lat', 'from_long', 'to_lat', 'to_long', 'Car_Cancellation',
       'dayofm', 'weekday', 'hour', 'from_lat_long', 'dummy_loc'],
      dtype='object')
```

CHECKING TRAFFIC BY LOCATION AND WEEKDAY

In [151]:
```
#Creating a dataframe for distinguishing LOCATION and WEEKDAY from others
df_analysis1 = df_final[['id', 'from_area_id', 'weekday','dummy_loc']]
```

In [152]:
```
#assigning the values in df_analysis1 a Unique ID.
df_analysis1_1 = df_analysis1.groupby(['from_area_id','weekday', 'dummy_loc'])['id'].count().reset_i
ndex()
```

In [153]:
```
#Assigning column names in the data frame.
df_analysis1_1.columns = ['from_area_id','weekday','dummy_loc', 'counts']
```

In [154]:
```
#sorting values as needed.
df_analysis1_1.sort_values('counts',  ascending = False).head(10)
```

Out[154]:

	from_area_id	weekday	dummy_loc	counts
747	393.0	6	Loc-462	680
741	393.0	0	Loc-462	610
745	393.0	4	Loc-462	575
746	393.0	5	Loc-462	563
744	393.0	3	Loc-462	490
743	393.0	2	Loc-462	481
742	393.0	1	Loc-462	459
1084	571.0	5	Loc-168	301
1083	571.0	4	Loc-168	256
1082	571.0	3	Loc-168	240

In [155]:
```
#Checking the lat and long on the particular location.
df1.iloc[462]
```

Out[155]:
```
from_lat      13.1996
from_long     77.7069
dummy_loc     Loc-462
Name: 462, dtype: object
```

From the above TABLE we infer that most cabs were booked from_area_id 393.0 on Loc-462(Lat-13.1996 , Long-77.7069)

CHECKING TRAFFIC BY LOCATION & HOUR

In [32]:
```
#Creating a dataframe for distinguishing LOCATION and HOUR from others
df_analysis2 = df_final[['id', 'hour', 'dummy_loc']]
```

In [75]:
```
#assigning the values in df_analysis2 a Unique ID.
df_analysis2_1 = df_analysis2.groupby(['hour', 'dummy_loc'])['id'].count().reset_index()
```

In [34]:
```
#Assigning column names in the data frame.
df_analysis2_1.columns = ['hour','dummy_loc', 'counts']
```

In [56]:
```
#sorting values as needed.
df_analysis2_1.sort_values(by = 'counts', ascending = False).head()
```

Out[56]:

	hour	dummy_loc	counts
6522	23	Loc-462	378
6281	22	Loc-462	320
2501	9	Loc-462	307
3380	12	Loc-462	287
5760	20	Loc-462	255

In [73]:
```
#Checking the lat and long on the particular location.
df1.iloc[462]
```

Out[73]:
```
from_lat      13.1996
from_long     77.7069
dummy_loc     Loc-462
Name: 462, dtype: object
```

The above table shows us that most cabs were booked at Loc-462(Lat-13.1996 , Long-77.7069) At 23:00.

CHECKING TRAFFIC BY LOCATION, HOUR & WEEKDAY

In [82]:
```
#Creating a dataframe for distinguishing LOCATION, HOUR and WEEKDAY from others
df_analysis3 = df_final[['id', 'weekday', 'hour', 'dummy_loc']]
```

In [83]:
```
#assigning the values in df_analysis3 a Unique ID.
df_analysis3_1 = df_analysis3.groupby(['weekday', 'hour','dummy_loc'])['id'].count().reset_index()
```

In [84]:
```
#Assigning column names in the data frame.
df_analysis3_1.columns = ['weekday','hour' , 'dummy_loc', 'counts' ]
```

In [85]:
```
#sorting values as needed.
df_analysis3_1.sort_values(by = 'counts', ascending = False).head()
```

Out[85]:

	weekday	hour	dummy_loc	counts
19117	6	23	Loc-462	86
2540	0	23	Loc-462	68
17821	6	12	Loc-462	62
18831	6	20	Loc-462	60
19030	6	22	Loc-462	57

In [86]:
```
#Checking the lat and long on the particular location.
df1.iloc[462]
```

Out[86]:
```
from_lat      13.1996
from_long     77.7069
dummy_loc     Loc-462
Name: 462, dtype: object
```

The above table shows us that most cabs were booked at Loc-462(Lat-13.1996 , Long-77.7069) At 23:00 on a Sunday.

CHECKING CANCELLATION ON THE BASIS OF FROM_AREA_ID

In [87]:
```
#information about car cancellation.
df.Car_Cancellation.value_counts()
```

Out[87]:
```
0    40299
1     3132
Name: Car_Cancellation, dtype: int64
```

In [88]:
```
#Creating a dataframe for distinguishing CAR_CANCELLATION & FROM_AREA_ID from others
df_analysis6 = df_final[['id', 'Car_Cancellation', 'from_area_id']]
```

In [89]:
```
#assigning the values in df_analysis6 a Unique ID.
df_analysis6_1 = df_analysis6.groupby(['Car_Cancellation', 'from_area_id'])['id'].count().reset_inde
x()
```

In [90]:
```
#Assigning column names in the data frame.
df_analysis6_1.columns = ['Car_Cancellation', 'from_area_id', 'counts' ]
```

In [223]:
```
#sorting values as needed.
df_analysis6_1.sort_values([ 'Car_Cancellation','counts'], ascending=[False, False]).head()
```

Out[223]:

	Car_Cancellation	from_area_id	counts
731	1	571.0	127
692	1	393.0	116
672	1	293.0	99
608	1	83.0	68
796	1	1010.0	53

The above table depicts that there were many cancellations from_area_id-571.0 and 393.0. Both the areas record cancellations above 100.

CHECKING CANCELLATION ON THE BASIS OF TIME, WEEKDAY, LOCATION AND FROM_AREA_ID

In [92]:
```
#Creating a dataframe for distinguishing CAR_CANCELLATION, WEEKDAY, HOUR, DUMMY LOC & FROM_AREA_ID f
rom others
df_analysis4 = df_final[['id', 'weekday','hour','Car_Cancellation', 'from_area_id' , 'dummy_loc']]
```

In [93]:
```
#assigning the values in df_analysis4 a Unique ID.
df_analysis4_1 = df_analysis4.groupby(['weekday','hour','Car_Cancellation', 'from_area_id', 'dummy_l
oc'])['id'].count().reset_index()
```

In [94]:
```
#Assigning column names in the data frame.
df_analysis4_1.columns = ['weekday','hour','Car_Cancellation', 'from_area_id', 'dummy_loc' , 'count
s' ]
```

In [95]:
```
#sorting values as needed.
df_analysis4_1.sort_values([ 'Car_Cancellation','counts'], ascending=[False, False]).head()
```

Out[95]:

	weekday	hour	Car_Cancellation	from_area_id	dummy_loc	counts
1705	0	12	1	393.0	Loc-462	9
2999	0	23	1	393.0	Loc-462	8
22266	6	23	1	393.0	Loc-462	8
14385	4	17	1	571.0	Loc-168	6
14604	4	18	1	571.0	Loc-168	6

From the above table we get to know that there were many cancellations from_area_id- 393.0 during midnight and then from_area_id-571.0 during the evening.

CHECKING CANCELLATION ON THE BASIS OF FROM_AREA_ID & LOCATION

In [96]:
```
#Creating a dataframe for distinguishing CAR_CANCELLATION, DUMMY_LOC & FROM_AREA_ID from others
df_analysis5 = df_final[['id', 'Car_Cancellation', 'from_area_id' , 'dummy_loc']]
```

In [97]:
```
#assigning the values in df_analysis5 a Unique ID.
df_analysis5_1 = df_analysis5.groupby(['Car_Cancellation', 'from_area_id', 'dummy_loc'])['id'].count
().reset_index()
```

In [98]:
```
#Assigning column names in the data frame.
df_analysis5_1.columns = ['Car_Cancellation', 'from_area_id', 'dummy_loc' , 'counts' ]
```

In [99]:
```
#sorting values as needed.
df_analysis5_1.sort_values([ 'Car_Cancellation','counts'], ascending=[False, False]).head()
```

Out[99]:

	Car_Cancellation	from_area_id	dummy_loc	counts
729	1	571.0	Loc-168	127
690	1	393.0	Loc-462	116
670	1	293.0	Loc-15	99
606	1	83.0	Loc-94	68
794	1	1010.0	Loc-227	53

From the above table we get to know that there were many cancellations from_area_id 571.0(Loc-168) and then from_area_id-393(Loc-462)

RESULTS

ANALYSIS

1. It's pretty clear that most cabs are booked on the weekends mainly, Friday and Saturday.

2. It's pretty clear that cabs are booked in the morning at 8:00,9:00 and in the evening at 17:00,18:00.

3. Through the Heatmap(Day&Hour) it's clear that cabs are booked at 8:00,9:00 in the morning and 17:00,18:00 in the evening mostly everyday.

4. We get to know that most cabs were booked was from_area_id- 393.0 on Loc-462(Lat-13.1996 , Long-77.7069) on a Sunday.

5. We get to know that most cabs were booked was from_area_id- 393.0 on Loc-462(Lat-13.1996 , Long-77.7069) at 23:00.

6. Most cabs were booked from_area_id-393.0 at Loc-462(Lat-13.1996 , Long-77.7069) at 23:00 on a Sunday.

7. We get to know that there were many cancellation from_area_id- 571.0(count-127) and then from_area_id- 393.0(count-116).

8. We get to know that there were many cancellations from_area_id-393.0 during midnight and then from_area_id-571.0 during the evening.

9.### WE GET TO KNOW THAT THERE WERE MANY CANCELLATION FROM_AREA_ID- 571.0 (LOC-168) AND THEN FROM_AREA_ID- 393.0 (LOC-462).

10. We can make out from the heatmap that most cabs in the area_id 393.0 are booked at 23:00 and during office commute hours.

11. We can make out of the heatmap that most cabs in the area_id 572.0 are booked at 6:00 and during office commute hours.

12. We can make out of the heatmap that most cabs in the area_id 293.0 are booked during office commute hours.

ADDITIONAL POINTS

1. More cabs can be deployed in the from_area_id-393.0 and from_area_id-571.0 during rush hours which are usually office hours namely :- 8:00-10:00 and 17:00-18:00 to incentivize the drivers.