

Delhivery - Business Case Study

Problem Statement

We have been given data on trips performed by parcels for Delhivery, which has attributes like trip_creation_time, routes, source and destination places, and open-source routing engine time. We need to clean, sanitize and manipulate data and get useful features and provide data to help them build forecasting models.

Importing required Python Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels
from scipy.special import comb
from scipy.stats import binom
from scipy.stats import norm,t
from scipy.stats import poisson, expon,geom, ttest_1samp,
ttest_ind,ttest_ind_from_stats,boxcox
from scipy.stats import shapiro, levene, kruskal, chi2,
chi2_contingency,pearsonr, spearmanr
from statsmodels.graphics.gofplots import qqplot
from sklearn.preprocessing import LabelEncoder, StandardScaler,
MinMaxScaler, OneHotEncoder
```

Loading our dataset

```
#Loading of csv file
df=pd.read_csv("delhivery_data.csv")
df
```

```
   data      trip_creation_time \
0  training  2018-09-20 02:35:36.476840
1  training  2018-09-20 02:35:36.476840
2  training  2018-09-20 02:35:36.476840
3  training  2018-09-20 02:35:36.476840
4  training  2018-09-20 02:35:36.476840
...
144862 training  2018-09-20 16:24:28.436231
144863 training  2018-09-20 16:24:28.436231
144864 training  2018-09-20 16:24:28.436231
144865 training  2018-09-20 16:24:28.436231
144866 training  2018-09-20 16:24:28.436231
```

route_schedule_uuid

route_type \		
0	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting
1	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting
2	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting
3	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting
4	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting
...
144862	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting
144863	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting
144864	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting
144865	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting
144866	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting

	trip_uuid	source_center	
source_name \			
0	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC
(Gujarat)			
1	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC
(Gujarat)			
2	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC
(Gujarat)			
3	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC
(Gujarat)			
4	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC
(Gujarat)			
...	
...			
144862	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H
(Haryana)			
144863	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H
(Haryana)			
144864	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H
(Haryana)			
144865	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H
(Haryana)			
144866	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H
(Haryana)			

destination_center	destination_name \
--------------------	--------------------

0	IND388620AAB	Khambhat_MotvdDPP_D	(Gujarat)
1	IND388620AAB	Khambhat_MotvdDPP_D	(Gujarat)
2	IND388620AAB	Khambhat_MotvdDPP_D	(Gujarat)
3	IND388620AAB	Khambhat_MotvdDPP_D	(Gujarat)
4	IND388620AAB	Khambhat_MotvdDPP_D	(Gujarat)

...
144862	IND000000ACB	Gurgaon_Bilaspur_HB	(Haryana)
144863	IND000000ACB	Gurgaon_Bilaspur_HB	(Haryana)
144864	IND000000ACB	Gurgaon_Bilaspur_HB	(Haryana)
144865	IND000000ACB	Gurgaon_Bilaspur_HB	(Haryana)
144866	IND000000ACB	Gurgaon_Bilaspur_HB	(Haryana)

		od_start_time	...	cutoff_timestamp	\
0	2018-09-20	03:21:32.418600	...	2018-09-20 04:27:55	
1	2018-09-20	03:21:32.418600	...	2018-09-20 04:17:55	
2	2018-09-20	03:21:32.418600	...	2018-09-20 04:01:19.505586	
3	2018-09-20	03:21:32.418600	...	2018-09-20 03:39:57	
4	2018-09-20	03:21:32.418600	...	2018-09-20 03:33:55	
...
144862	2018-09-20	16:24:28.436231	...	2018-09-20 21:57:20	
144863	2018-09-20	16:24:28.436231	...	2018-09-20 21:31:18	
144864	2018-09-20	16:24:28.436231	...	2018-09-20 21:11:18	
144865	2018-09-20	16:24:28.436231	...	2018-09-20 20:53:19	
144866	2018-09-20	16:24:28.436231	...	2018-09-20 16:24:28.436231	

	actual_distance_to_destination	actual_time	osrm_time
osrm_distance \			
0	10.435660	14.0	11.0
11.9653			
1	18.936842	24.0	20.0
21.7243			
2	27.637279	40.0	28.0
32.5395			
3	36.118028	62.0	40.0
45.5620			
4	39.386040	68.0	44.0
54.2181			
...
...			
144862	45.258278	94.0	60.0
67.9280			
144863	54.092531	120.0	76.0
85.6829			
144864	66.163591	140.0	88.0
97.0933			
144865	73.680667	158.0	98.0
111.2709			
144866	70.039010	426.0	95.0
88.7319			

1	trip_creation_time	144867	non-null	object
2	route_schedule_uuid	144867	non-null	object
3	route_type	144867	non-null	object
4	trip_uuid	144867	non-null	object
5	source_center	144867	non-null	object
6	source_name	144574	non-null	object
7	destination_center	144867	non-null	object
8	destination_name	144606	non-null	object
9	od_start_time	144867	non-null	object
10	od_end_time	144867	non-null	object
11	start_scan_to_end_scan	144867	non-null	float64
12	is_cutoff	144867	non-null	bool
13	cutoff_factor	144867	non-null	int64
14	cutoff_timestamp	144867	non-null	object
15	actual_distance_to_destination	144867	non-null	float64
16	actual_time	144867	non-null	float64
17	osrm_time	144867	non-null	float64
18	osrm_distance	144867	non-null	float64
19	factor	144867	non-null	float64
20	segment_actual_time	144867	non-null	float64
21	segment_osrm_time	144867	non-null	float64
22	segment_osrm_distance	144867	non-null	float64
23	segment_factor	144867	non-null	float64

dtypes: bool(1), float64(10), int64(1), object(12)

memory usage: 25.6+ MB

df.nunique() *# number of unique values in columns*

data	2
trip_creation_time	14817
route_schedule_uuid	1504
route_type	2
trip_uuid	14817
source_center	1508
source_name	1498
destination_center	1481
destination_name	1468
od_start_time	26369
od_end_time	26369
start_scan_to_end_scan	1915
is_cutoff	2
cutoff_factor	501
cutoff_timestamp	93180
actual_distance_to_destination	144515
actual_time	3182
osrm_time	1531
osrm_distance	138046
factor	45641
segment_actual_time	747
segment_osrm_time	214

```
segment_osrm_distance      113799
segment_factor              5675
dtype: int64
```

```
df.isna().sum() #missing values in columns
```

```
data                0
trip_creation_time  0
route_schedule_uuid 0
route_type          0
trip_uuid           0
source_center       0
source_name         293
destination_center  0
destination_name     261
od_start_time       0
od_end_time         0
start_scan_to_end_scan 0
is_cutoff           0
cutoff_factor       0
cutoff_timestamp    0
actual_distance_to_destination 0
actual_time         0
osrm_time           0
osrm_distance       0
factor              0
segment_actual_time 0
segment_osrm_time   0
segment_osrm_distance 0
segment_factor      0
dtype: int64
```

```
df.describe() #Statistical summary of the dataset
```

	start_scan_to_end_scan	cutoff_factor
actual_distance_to_destination \		
count	144867.000000	144867.000000
144867.000000		
mean	961.262986	232.926567
234.073372		
std	1037.012769	344.755577
344.990009		
min	20.000000	9.000000
9.000045		
25%	161.000000	22.000000
23.355874		
50%	449.000000	66.000000
66.126571		
75%	1634.000000	286.000000
286.708875		

```
max          7898.000000    1927.000000
1927.447705
```

```
      actual_time    osrm_time  osrm_distance    factor \
count  144867.000000  144867.000000  144867.000000  144867.000000
mean    416.927527    213.868272    284.771297    2.120107
std     598.103621    308.011085    421.119294    1.715421
min      9.000000      6.000000     9.008200     0.144000
25%     51.000000     27.000000    29.914700    1.604264
50%    132.000000     64.000000    78.525800    1.857143
75%    513.000000    257.000000   343.193250    2.213483
max    4532.000000   1686.000000  2326.199100   77.387097
```

```
      segment_actual_time  segment_osrm_time
segment_osrm_distance \
count    144867.000000    144867.000000    144867.000000

mean           36.196111           18.507548           22.82902
std            53.571158           14.775960           17.86066
min            -244.000000           0.000000           0.00000
25%            20.000000           11.000000           12.07010
50%            29.000000           17.000000           23.51300
75%            40.000000           22.000000           27.81325
max            3051.000000          1611.000000          2191.40370
```

```
      segment_factor
count  144867.000000
mean    2.218368
std     4.847530
min     -23.444444
25%     1.347826
50%     1.684211
75%     2.250000
max     574.250000
```

```
df.describe(include=object)
```

```
      data      trip_creation_time \
count    144867          144867
unique         2          14817
top  training  2018-09-28 05:23:15.359220
freq    104858          101
```

```
route_schedule_uuid
```

route_type \		
count	144867	144867
unique	1504	2
top	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL
freq	1812	99660

	trip_uuid	source_center
source_name \		
count	144867	144867
144574		
unique	14817	1508
1498		
top	trip-153811219535896559	IND000000ACB Gurgaon_Bilaspur_HB (Haryana)
freq	101	23347
23347		

	destination_center	destination_name \
count	144867	144606
unique	1481	1468
top	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)
freq	15192	15192

	od_start_time	od_end_time \
count	144867	144867
unique	26369	26369
top	2018-09-21 18:37:09.322207	2018-09-24 09:59:15.691618
freq	81	81

	cutoff_timestamp
count	144867
unique	93180
top	2018-09-24 05:19:20
freq	40

#Checking for source center value for which source name is null

```
df[(df["source_name"].notnull()) &
(df["source_center"].isin(df[df["source_name"].isnull()]
["source_center"]))]
```

Empty DataFrame

Columns: [data, trip_creation_time, route_schedule_uuid, route_type, trip_uuid, source_center, source_name, destination_center, destination_name, od_start_time, od_end_time, start_scan_to_end_scan, is_cutoff, cutoff_factor, cutoff_timestamp, actual_distance_to_destination, actual_time, osrm_time, osrm_distance,


```
factor, segment_actual_time, segment_osrm_time, segment_osrm_distance,
segment_factor]
Index: []
```

```
[0 rows x 24 columns]
```

```
#Checking for destination center value for which destination name is null
```

```
df[(df["destination_name"].notnull()) &
(df["destination_center"].isin(df[df["destination_name"].isnull()]
["destination_center"]))]
```

```
Empty DataFrame
```

```
Columns: [data, trip_creation_time, route_schedule_uuid, route_type,
trip_uuid, source_center, source_name, destination_center,
destination_name, od_start_time, od_end_time, start_scan_to_end_scan,
is_cutoff, cutoff_factor, cutoff_timestamp,
actual_distance_to_destination, actual_time, osrm_time, osrm_distance,
factor, segment_actual_time, segment_osrm_time, segment_osrm_distance,
segment_factor]
Index: []
```

```
[0 rows x 24 columns]
```

```
#Here we can observe that minimum value of segment_actual_time and
segment_factor is negative,
#which seems false values as time can not be negative, so we will drop
that data
```

```
df.drop(df[df["segment_actual_time"]<0].index, inplace=True)
```

```
df.describe()
```

	start_scan_to_end_scan	cutoff_factor
actual_distance_to_destination \		
count	144846.000000	144846.000000
144846.000000		
mean	961.226537	232.911057
234.057171		
std	1036.993595	344.740981
344.974984		
min	20.000000	9.000000
9.000045		
25%	161.000000	22.000000
23.354927		
50%	449.000000	66.000000
66.126234		
75%	1634.000000	286.000000
286.706673		
max	7898.000000	1927.000000
1927.447705		

	actual_time	osrm_time	osrm_distance	factor \
count	144846.000000	144846.000000	144846.000000	144846.000000
mean	416.908724	213.853002	284.750969	2.120190
std	598.085058	307.997702	421.101831	1.715508
min	9.000000	6.000000	9.008200	0.144000
25%	51.000000	27.000000	29.909925	1.604288
50%	132.000000	64.000000	78.524600	1.857143
75%	513.000000	257.000000	343.062075	2.213589
max	4532.000000	1686.000000	2326.199100	77.387097

	segment_actual_time	segment_osrm_time	
segment_osrm_distance \			
count	144846.000000	144846.000000	144846.000000
mean	36.207427	18.507304	22.828528
std	53.561259	14.775870	17.860268
min	0.000000	0.000000	0.000000
25%	20.000000	11.000000	12.070100
50%	29.000000	17.000000	23.513000
75%	40.000000	22.000000	27.812975
max	3051.000000	1611.000000	2191.403700

	segment_factor
count	144846.000000
mean	2.219084
std	4.847144
min	-1.000000
25%	1.347826
50%	1.684211
75%	2.250000
max	574.250000

Dataset Information

data: It contains whether the data is testing or training type

trip_creation_time: It is the timestamp of trip_creation. It ranges from '2018-09-12 00:25:19.499696' to '2018-10-03 23:59:42.701692'

oute_schedule_uuid: it is unique_id for particular route schedule

route type: It contains whether the route is Full Truck Load or Carting type

trip_uuid: It is a unique id associated with a particular trip

source_center: It is the ID of the origin of the trip

source_name: Its the name of the origin of the trip

destination_center: It is the ID of the destination of the trip

destination_name: It is the name of the destination of the trip

od_start_time: It is the trip start time

od_end_time: It is the trip end time

Start_scan_to_end_scan: It gives the time taken to deliver from source to destination. It ranges from 20 to 7898.

is_cutoff: It is an unknown field, which is boolean

cutoff_factor: It is the rounded value of the actual_distance_to_destination, it ranges from 9 to 1927

cutoff_timestamp: It is an unknown field

actual_distance_to_destination: It is the distance between the source and destination warehouses, it ranges from 9.00 to 1927.44

actual_time: It contains the actual time taken to complete the delivery (cumulative), it ranges from 9 to 4532.

osrm_time: It is an open-source routing engine time calculator which computes the shortest path between points in a given map and gives the time (cumulative), it ranges from 6 to 1686

osrm_distance: It contains the distance to the destination based on osrm, it ranges from 9.00 to 2326.199

factor: It is a ratio of actual_time to osrm_time, it ranges from 0.144 to 77.38.

segment_actual_time: It is a segment time, a time taken by a subset of package delivery, It ranges from -244 to 3051

segment_osrm_time: It contains the osrm time taken by a subset of the package delivery. It ranges from 0 to 1611

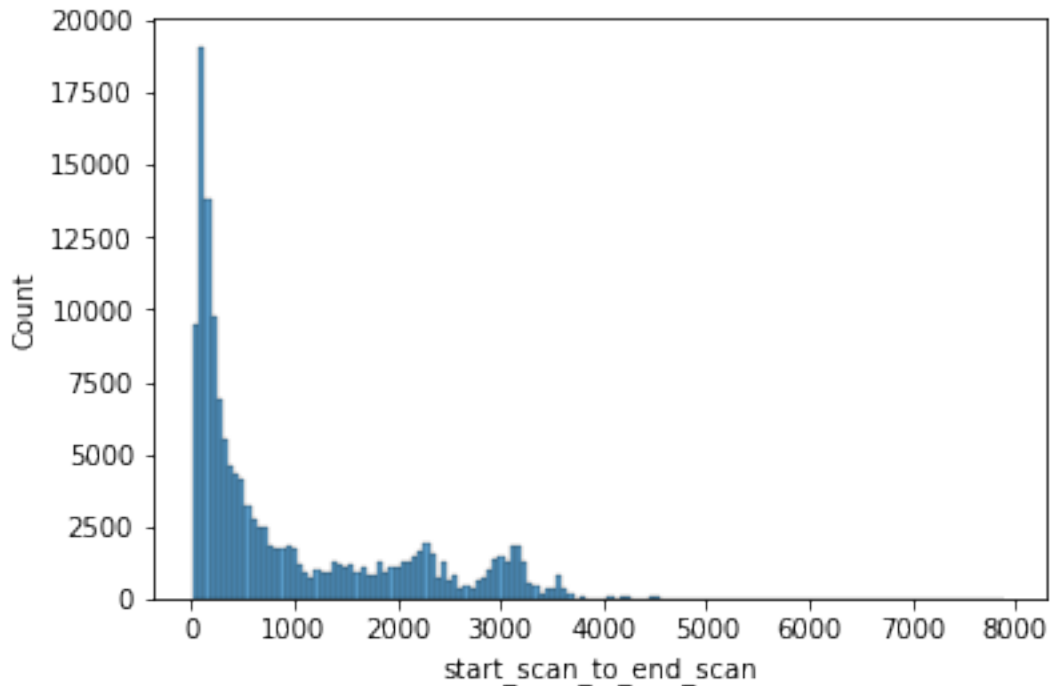
segment_osrm_distance: It contains OSRM distance, the distance covered by a subset of package delivery, it ranges from 0 to 2191.40

segment_factor: It is a ratio between segment_actual_time to segment_osrm_time, it ranges from -23.544 to 574.25

Univariate Analysis

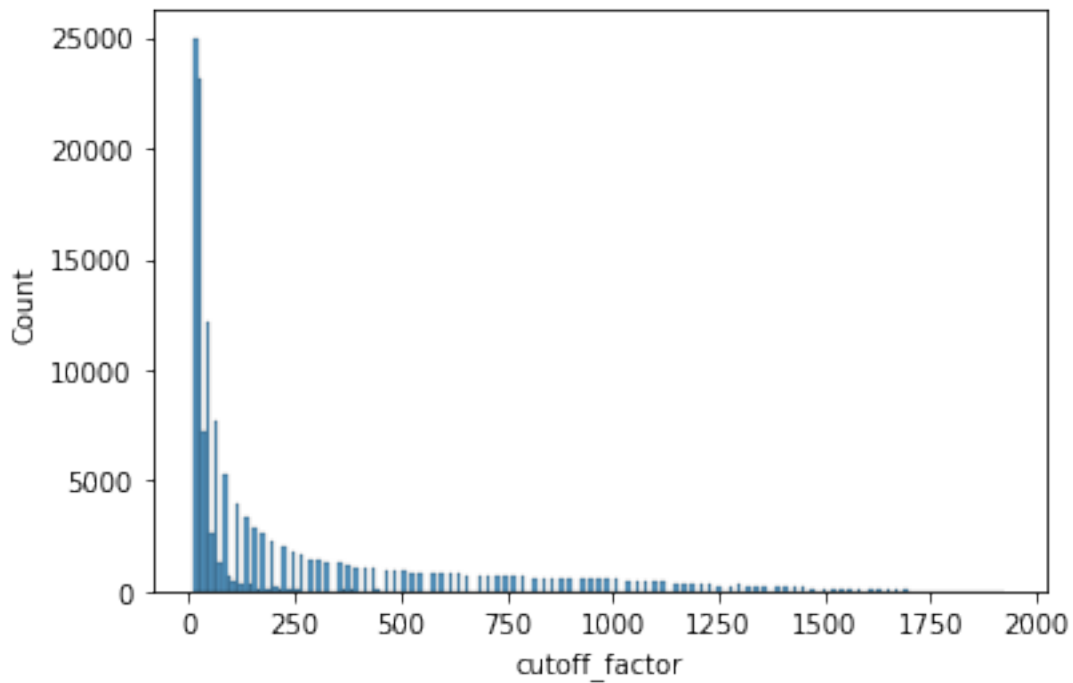
```
#Histogram for start_to_scan_to_end_scan attribute  
sns.histplot(df["start_scan_to_end_scan"])
```

```
<AxesSubplot: xlabel='start_scan_to_end_scan', ylabel='Count'>
```

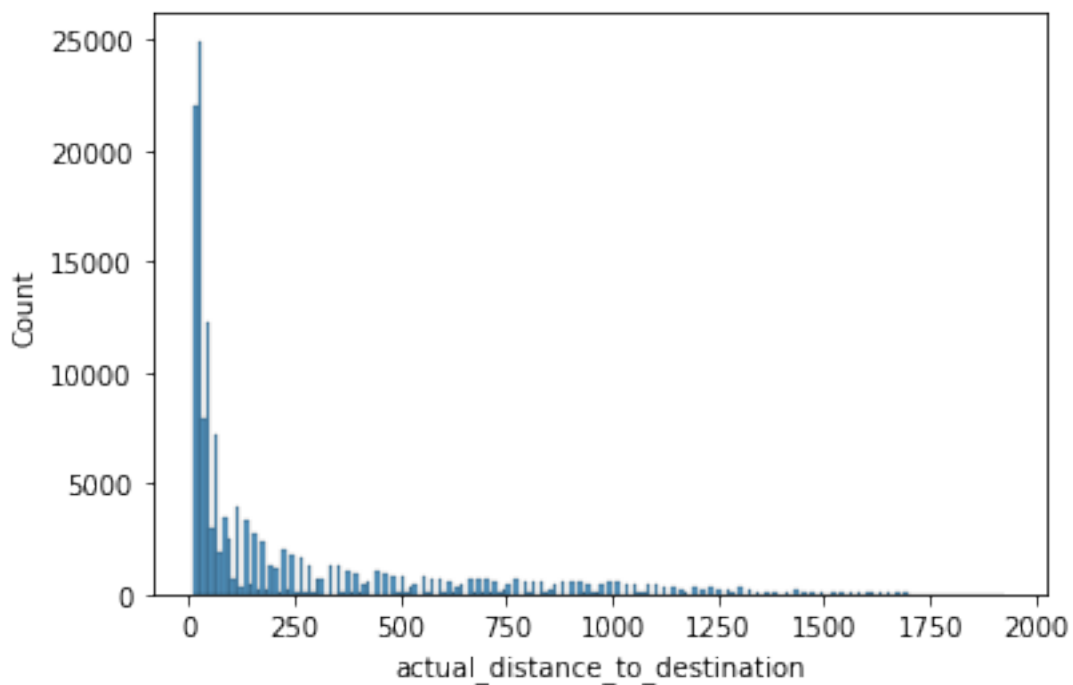


```
#Histogram for cutoff_factor attribute  
sns.histplot(df["cutoff_factor"])
```

```
<AxesSubplot: xlabel='cutoff_factor', ylabel='Count'>
```

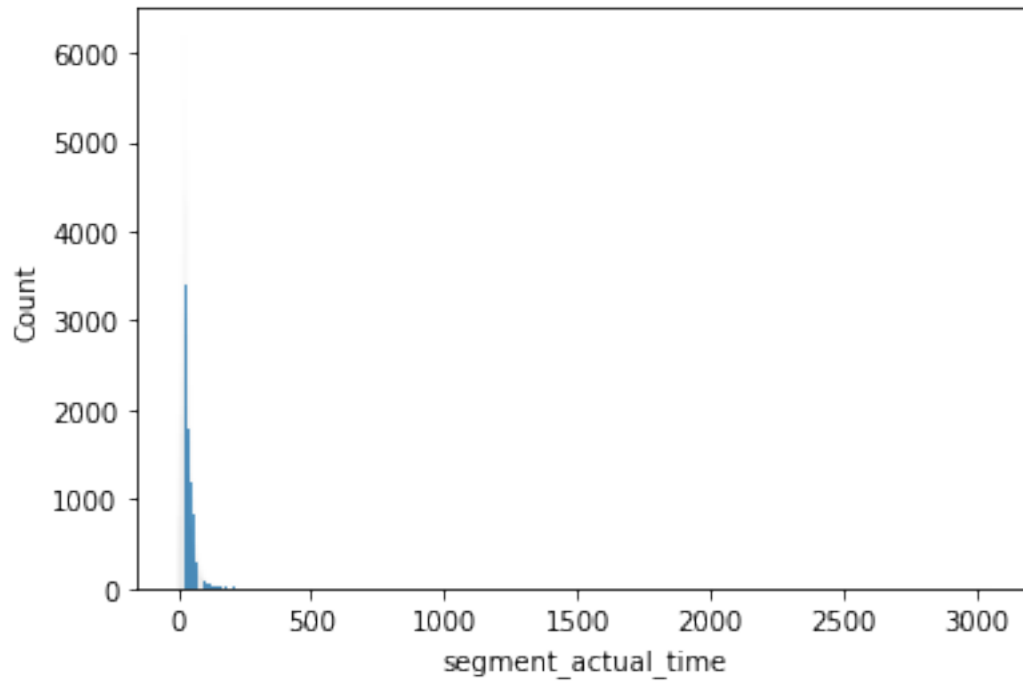


```
#Histogram for actual_distance_to_destination attribute  
sns.histplot(df["actual_distance_to_destination"])  
<AxesSubplot: xlabel='actual_distance_to_destination', ylabel='Count'>
```



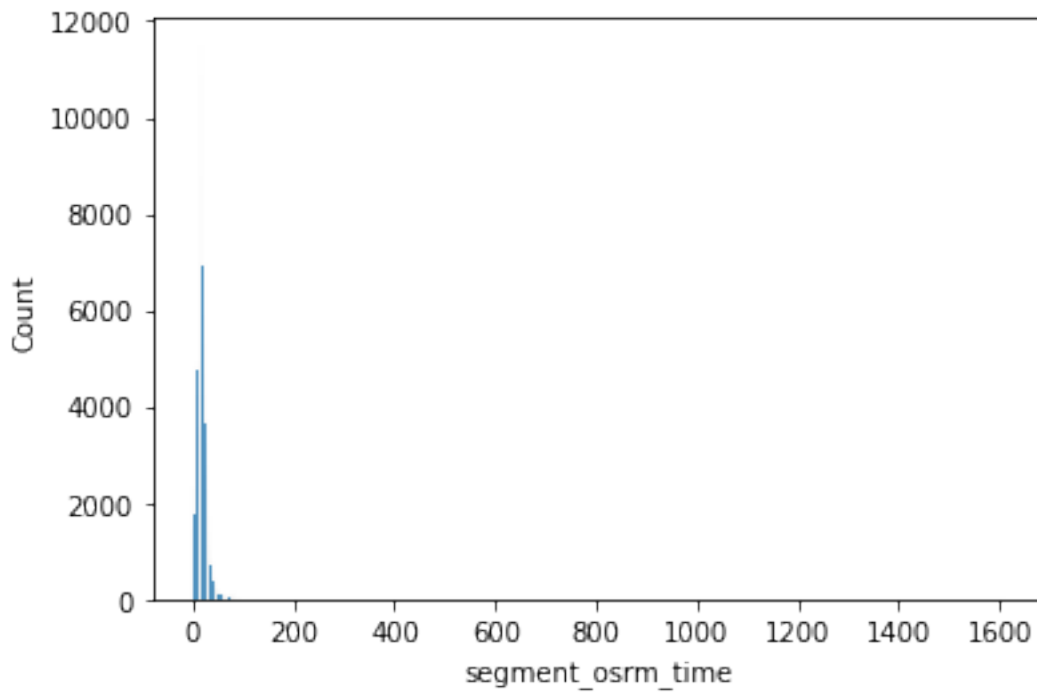
```
#Histogram for segment_actual_time attribute  
sns.histplot(df["segment_actual_time"])
```

```
<AxesSubplot: xlabel='segment_actual_time', ylabel='Count'>
```

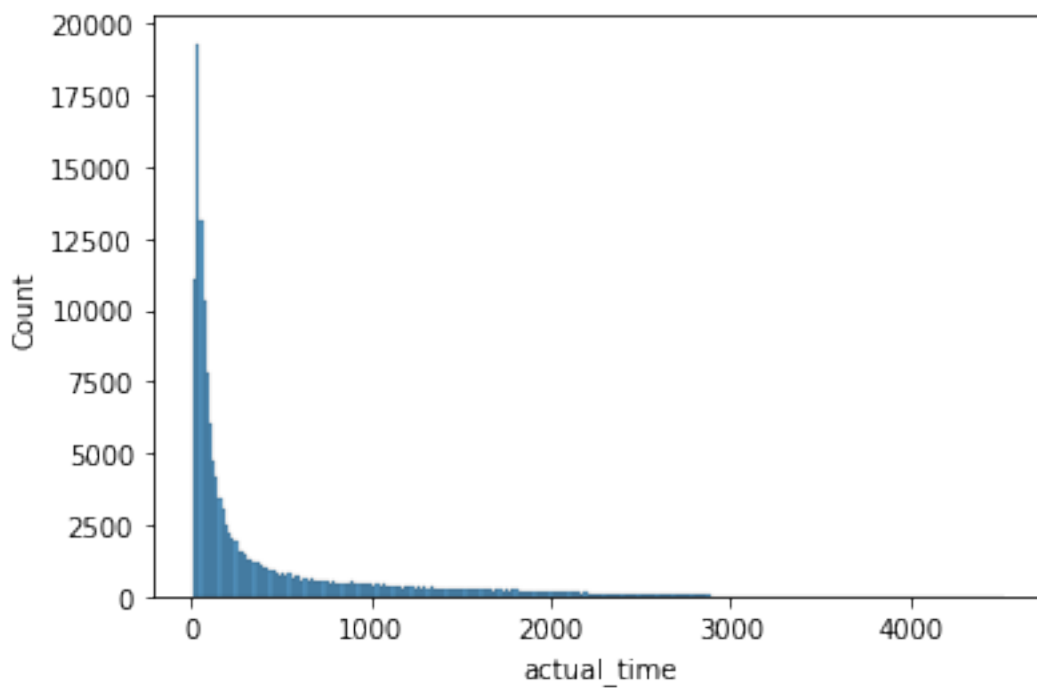


```
#Histogram for segment_osrm_time attribute  
sns.histplot(df["segment_osrm_time"])
```

```
<AxesSubplot: xlabel='segment_osrm_time', ylabel='Count'>
```

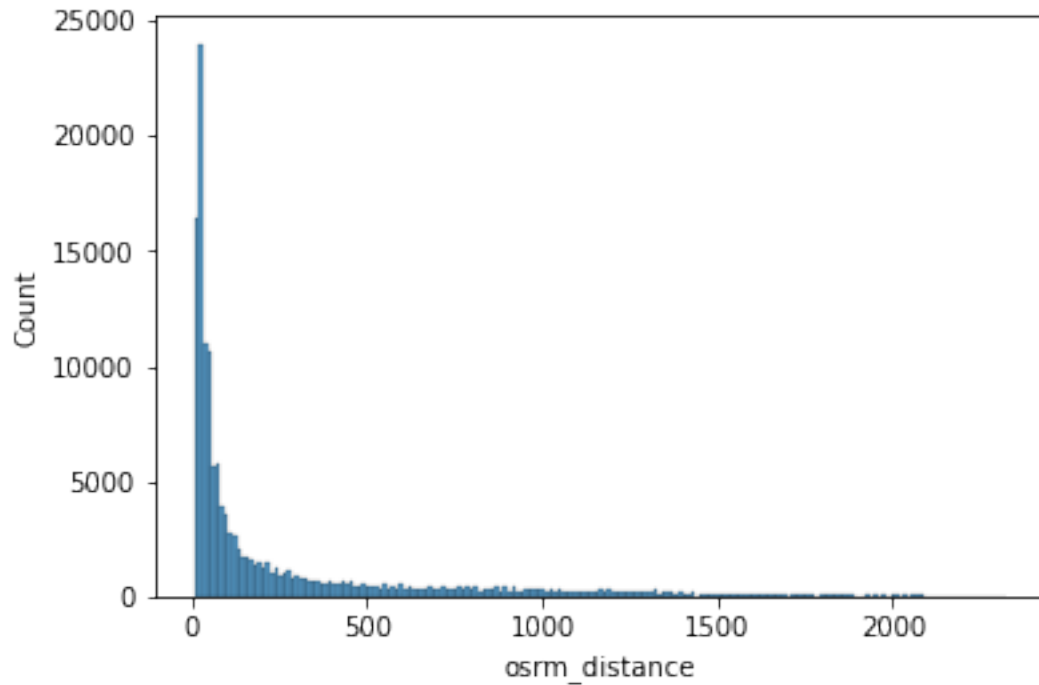


```
#Histogram for actual_time attribute  
sns.histplot(df["actual_time"])  
  
<AxesSubplot: xlabel='actual_time', ylabel='Count'>
```



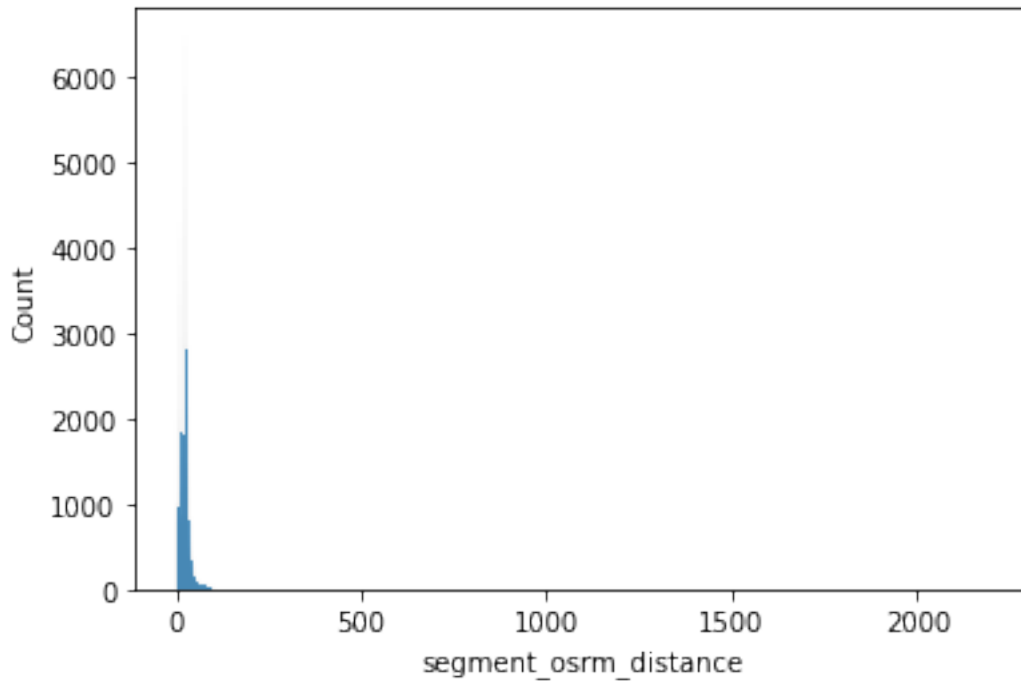
```
#Histogram for osrm_distance attribute  
sns.histplot(df["osrm_distance"])
```

```
<AxesSubplot: xlabel='osrm_distance', ylabel='Count'>
```



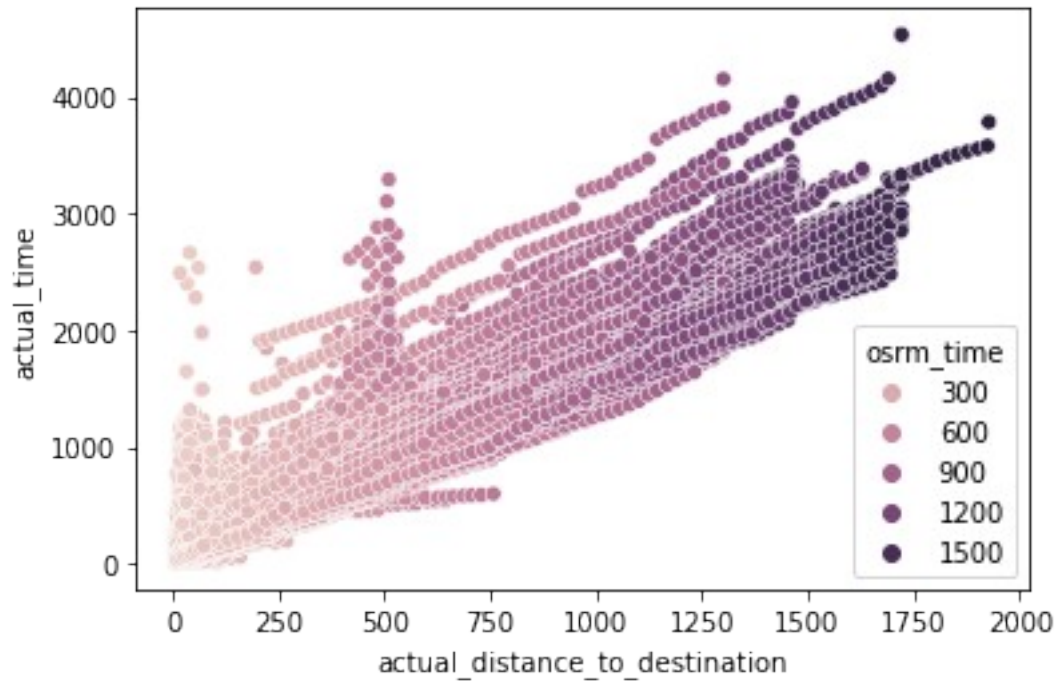
```
#Histogram for segment_osrm_distance attribute  
sns.histplot(df["segment_osrm_distance"])
```

```
<AxesSubplot: xlabel='segment_osrm_distance', ylabel='Count'>
```

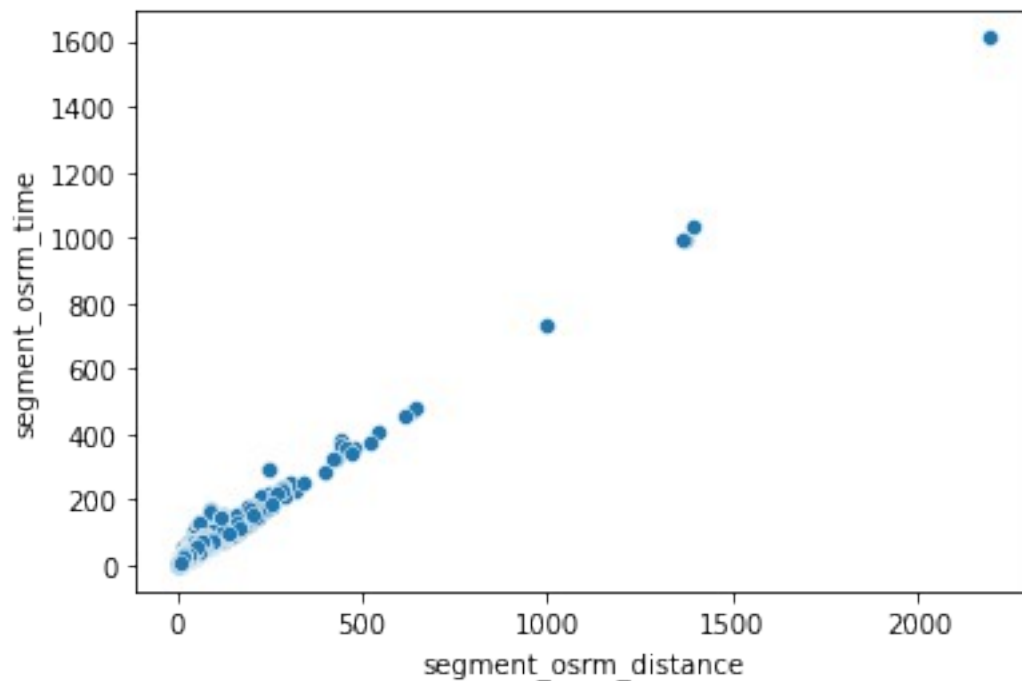
Bivariate Analysis

```
#Scatterplot between actual-distance_to_destination, actual_time and osrm_time  
sns.scatterplot(data=df,  
x="actual_distance_to_destination",y="actual_time", hue="osrm_time")  
<AxesSubplot: xlabel='actual_distance_to_destination',  
ylabel='actual_time'>
```



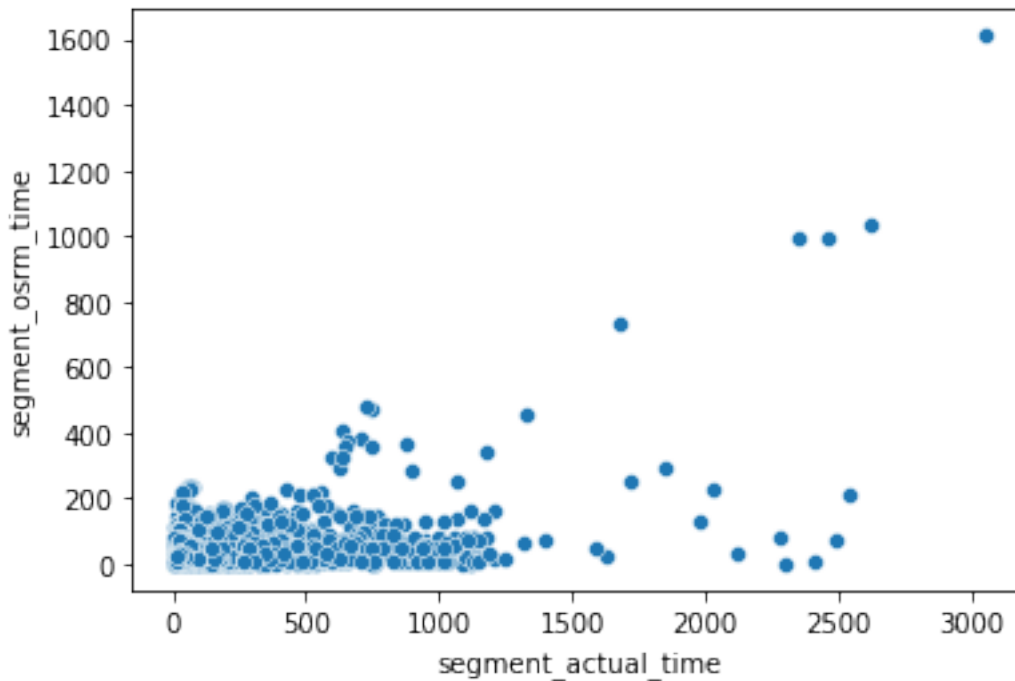
```
#scatterplot between segment_osrm_distance and segment_osrm_time
sns.scatterplot(data=df,
x="segment_osrm_distance",y="segment_osrm_time")

<AxesSubplot: xlabel='segment_osrm_distance',
ylabel='segment_osrm_time'>
```



```
#scatterplot between segment_actual_time and segment_osrm_time
sns.scatterplot(data=df,
x="segment_actual_time",y="segment_osrm_time")

<AxesSubplot: xlabel='segment_actual_time',
ylabel='segment_osrm_time'>
```



```
#correlation in dataframe
df.corr()
```

C:\Users\Pipaliya\AppData\Local\Temp\ipykernel_8836\2340352341.py:2:
FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

```
df.corr()
```

	start_scan_to_end_scan	is_cutoff	\
start_scan_to_end_scan	1.000000	0.299115	
is_cutoff	0.299115	1.000000	
cutoff_factor	0.784656	0.190819	
actual_distance_to_destination	0.784988	0.191574	
actual_time	0.785924	0.168270	
osrm_time	0.785283	0.186485	
osrm_distance	0.784120	0.188247	
factor	-0.023192	-0.121369	
segment_actual_time	0.093372	-0.006945	
segment_osrm_time	0.219844	0.216334	

segment_osrm_distance	0.306972	0.254661
segment_factor	-0.020225	-0.106518

	cutoff_factor
--	---------------

actual_distance_to_destination \	
start_scan_to_end_scan	0.784656

0.784988

is_cutoff	0.190819
-----------	----------

0.191574

cutoff_factor	1.000000
---------------	----------

0.999986

actual_distance_to_destination	0.999986
--------------------------------	----------

1.000000

actual_time	0.978719
-------------	----------

0.978658

osrm_time	0.995833
-----------	----------

0.995872

osrm_distance	0.997116
---------------	----------

0.997148

factor	-0.064559	-
--------	-----------	---

0.064743

segment_actual_time	0.045063
---------------------	----------

0.045320

segment_osrm_time	0.157942
-------------------	----------

0.158836

segment_osrm_distance	0.231109
-----------------------	----------

0.232119

segment_factor	-0.031439	-
----------------	-----------	---

0.031588

	actual_time	osrm_time	osrm_distance
--	-------------	-----------	---------------

\

start_scan_to_end_scan	0.785924	0.785283	0.784120
------------------------	----------	----------	----------

is_cutoff	0.168270	0.186485	0.188247
-----------	----------	----------	----------

cutoff_factor	0.978719	0.995833	0.997116
---------------	----------	----------	----------

actual_distance_to_destination	0.978658	0.995872	0.997148
--------------------------------	----------	----------	----------

actual_time	1.000000	0.977996	0.979398
-------------	----------	----------	----------

osrm_time	0.977996	1.000000	0.999119
-----------	----------	----------	----------

osrm_distance	0.979398	0.999119	1.000000
---------------	----------	----------	----------

factor	0.033498	-0.069081	-0.065391
--------	----------	-----------	-----------

segment_actual_time	0.124483	0.049977	0.048787
---------------------	----------	----------	----------

segment_osrm_time	0.171480	0.177074	0.169157
segment_osrm_distance	0.242296	0.242288	0.239672
segment_factor	0.017570	-0.033038	-0.031786

	factor	segment_actual_time \
start_scan_to_end_scan	-0.023192	0.093372
is_cutoff	-0.121369	-0.006945
cutoff_factor	-0.064559	0.045063
actual_distance_to_destination	-0.064743	0.045320
actual_time	0.033498	0.124483
osrm_time	-0.069081	0.049977
osrm_distance	-0.065391	0.048787
factor	1.000000	0.518451
segment_actual_time	0.518451	1.000000
segment_osrm_time	-0.053154	0.433604
segment_osrm_distance	-0.036724	0.449167
segment_factor	0.540448	0.483699

	segment_osrm_time	
segment_osrm_distance \		
start_scan_to_end_scan	0.219844	
0.306972		
is_cutoff	0.216334	
0.254661		
cutoff_factor	0.157942	
0.231109		
actual_distance_to_destination	0.158836	
0.232119		
actual_time	0.171480	
0.242296		
osrm_time	0.177074	
0.242288		
osrm_distance	0.169157	
0.239672		
factor	-0.053154	-
0.036724		
segment_actual_time	0.433604	
0.449167		
segment_osrm_time	1.000000	
0.948520		
segment_osrm_distance	0.948520	
1.000000		
segment_factor	-0.068472	-
0.059317		

	segment_factor
start_scan_to_end_scan	-0.020225

is_cutoff	-0.106518
cutoff_factor	-0.031439
actual_distance_to_destination	-0.031588
actual_time	0.017570
osrm_time	-0.033038
osrm_distance	-0.031786
factor	0.540448
segment_actual_time	0.483699
segment_osrm_time	-0.068472
segment_osrm_distance	-0.059317
segment_factor	1.000000

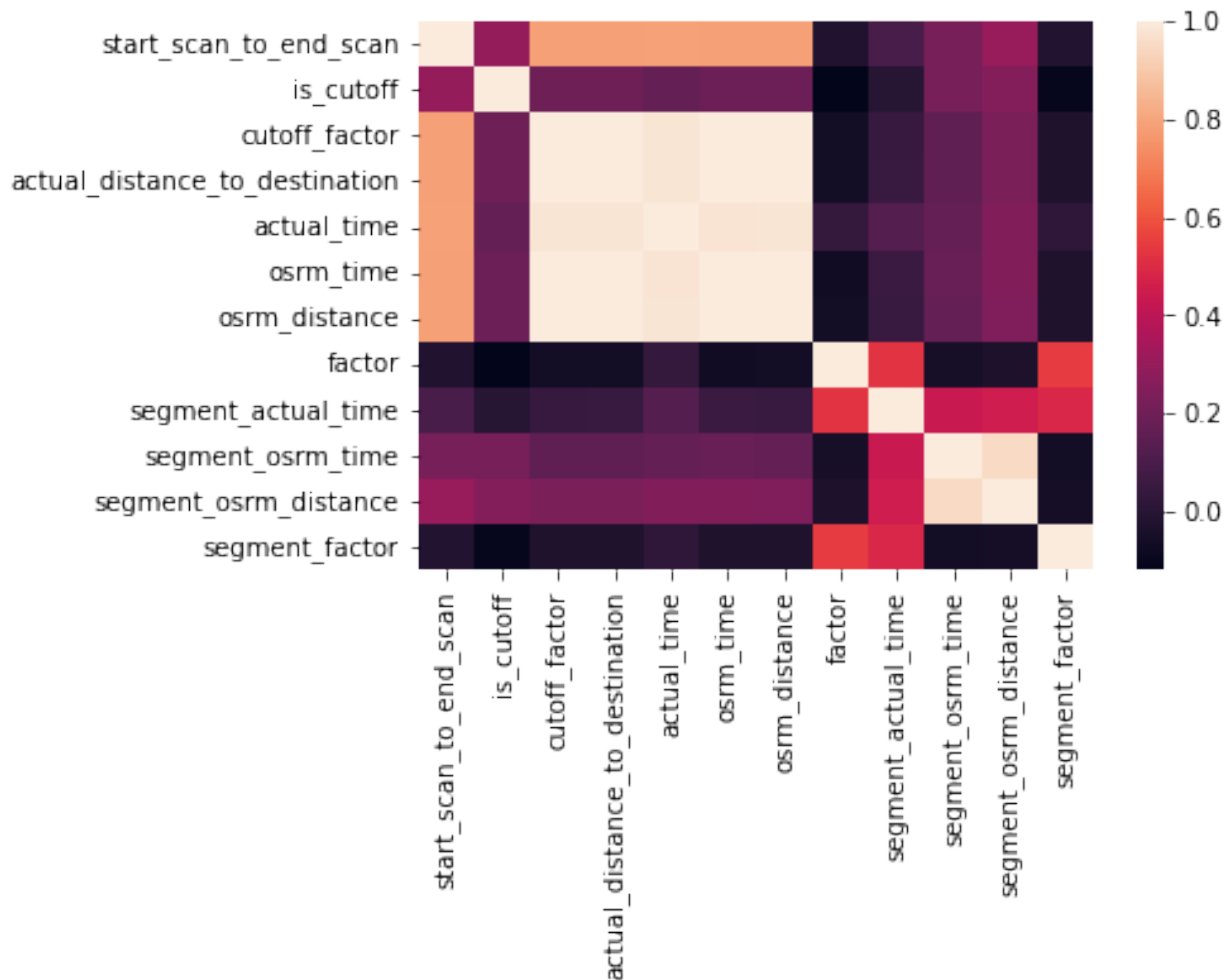
#heatmap of dataframe

```
sns.heatmap(df.corr())
```

C:\Users\Pipaliya\AppData\Local\Temp\ipykernel_8836\3354145055.py:2:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only
valid columns or specify the value of numeric_only to silence this
warning.

```
sns.heatmap(df.corr())
```

<AxesSubplot: >



Data Wrangling

```
#merging of rows based on trip_id and source and destination details
data=df.groupby(["route_type","trip_uuid","trip_creation_time","source_center","source_name","destination_center","destination_name","od_start_time","od_end_time","start_scan_to_end_scan"]).aggregate({"cutoff_factor":"max","actual_distance_to_destination":"max","segment_actual_time":"sum","segment_osrm_time":"sum","actual_time":"max","osrm_time":"max","osrm_distance":"max","segment_osrm_distance":"sum"}).reset_index()
data
```

	route_type	trip_uuid	trip_creation_time
0	Carting	trip-153671042288605164	2018-09-12 00:00:22.886430
1	Carting	trip-153671042288605164	2018-09-12 00:00:22.886430

2	Carting	trip-153671046011330457	2018-09-12 00:01:00.113710
3	Carting	trip-153671055416136166	2018-09-12 00:02:34.161600
4	Carting	trip-153671055416136166	2018-09-12 00:02:34.161600
...
26218	FTL	trip-153861014185597051	2018-10-03 23:42:21.856227
26219	FTL	trip-153861023893369544	2018-10-03 23:43:58.933947
26220	FTL	trip-153861023893369544	2018-10-03 23:43:58.933947
26221	FTL	trip-153861118270144424	2018-10-03 23:59:42.701692
26222	FTL	trip-153861118270144424	2018-10-03 23:59:42.701692

	source_center	source_name
destination_center \		
0	IND561203AAB	Doddablpur_ChikaDPP_D (Karnataka)
	IND562101AAA	
1	IND572101AAA	Tumkur_Veersagr_I (Karnataka)
	IND561203AAB	
2	IND400072AAB	Mumbai Hub (Maharashtra)
	IND401104AAA	
3	IND600056AAA	Chennai_Poonamallee (Tamil Nadu)
	IND602105AAB	
4	IND600116AAB	Chennai_Porur_DPC (Tamil Nadu)
	IND600056AAA	
...
...		
26218	IND462022AAA	Bhopal_Trnsport_H (Madhya Pradesh)
	IND209304AAA	
26219	IND382715AAA	Kadi_KaranNGR_D (Gujarat)
	IND382430AAB	
26220	IND384205AAA	Mehsana_Panchot_IP (Gujarat)
	IND382715AAA	
26221	IND583119AAA	Sandur_WrdN1DPP_D (Karnataka)
	IND583101AAA	
26222	IND583201AAA	Hospet (Karnataka)
	IND583119AAA	

	destination_name	
od_start_time \		
0	Chikblapur_ShntiSgr_D (Karnataka)	2018-09-12
	02:03:09.655591	
1	Doddablpur_ChikaDPP_D (Karnataka)	2018-09-12
	00:00:22.886430	

2	Mumbai_MiraRd_IP (Maharashtra)	2018-09-12
00:01:00.113710		
3	Chennai_Sriperumbudur_Dc (Tamil Nadu)	2018-09-12
02:12:10.755603		
4	Chennai_Poonamallee (Tamil Nadu)	2018-09-12
00:02:34.161600		
...
..		
26218	Kanpur_Central_H_6 (Uttar Pradesh)	2018-10-03
23:42:21.856227		
26219	Ahmedabad_East_H_1 (Gujarat)	2018-10-04
01:48:54.382343		
26220	Kadi_KaranNGR_D (Gujarat)	2018-10-03
23:43:58.933947		
26221	Bellary_Dc (Karnataka)	2018-10-04
03:58:40.726547		
26222	Sandur_WrdN1DPP_D (Karnataka)	2018-10-04
02:51:44.712656		

	od_end_time	start_scan_to_end_scan
cutoff_factor \		
0	2018-09-12 03:01:59.598855	58.0
24		
1	2018-09-12 02:03:09.655591	122.0
48		
2	2018-09-12 01:41:29.809822	100.0
17		
3	2018-09-12 03:13:03.432532	60.0
15		
4	2018-09-12 02:12:10.755603	129.0
9		
...
..		

26218	2018-10-04 19:57:34.928573	1215.0
442		
26219	2018-10-04 04:01:41.425627	132.0
50		
26220	2018-10-04 01:48:54.382343	124.0
34		
26221	2018-10-04 08:46:09.166940	287.0
40		
26222	2018-10-04 03:58:40.726547	66.0
25		

	actual_distance_to_destination	segment_actual_time
segment_osrm_time \		
0	24.644021	46.0
26.0		
1	48.542890	95.0

39.0		
2	17.175274	59.0
16.0		
3	15.325529	39.0
12.0		
4	9.271519	21.0
11.0		
...
...		
26218	442.024575	991.0
425.0		
26219	50.473578	129.0
55.0		
26220	34.270235	57.0
37.0		
26221	40.546740	233.0
42.0		
26222	25.534793	41.0
25.0		

	actual_time	osrm_time	osrm_distance	segment_osrm_distance
0	47.0	26.0	28.1994	28.1995
1	96.0	42.0	56.9116	55.9899
2	59.0	15.0	19.6800	19.8766
3	40.0	12.0	16.2225	16.2225
4	21.0	11.0	11.8422	11.8422
...
26218	997.0	395.0	545.1256	573.6479
26219	130.0	54.0	61.9571	67.2659
26220	57.0	38.0	40.4257	40.4256
26221	233.0	42.0	52.5303	52.5303
26222	42.0	26.0	28.0484	28.0484

[26223 rows x 18 columns]

#Merging rows based on trip_id

```
data=data.groupby(["route_type","trip_uuid","trip_creation_time"]).agg(
    regate({"source_center":"first","source_name":"first","destination_center":"last",
            "destination_name":"last",
            "od_start_time":"first",
            "od_end_time":"last","cutoff_factor":"sum","actual_distance_to_destination":"sum","osrm_distance":"sum",
            "start_scan_to_end_scan":"sum",
            "segment_actual_time":"sum",
            "segment_osrm_time":"sum","actual_time":"sum",
```

```
"osrm_time":"sum","segment_osrm_distance":"sum"}).reset_index()
data
```

	route_type	trip_uuid	trip_creation_time
\			
0	Carting	trip-153671042288605164	2018-09-12 00:00:22.886430
1	Carting	trip-153671046011330457	2018-09-12 00:01:00.113710
2	Carting	trip-153671055416136166	2018-09-12 00:02:34.161600
3	Carting	trip-153671066201138152	2018-09-12 00:04:22.011653
4	Carting	trip-153671066826362165	2018-09-12 00:04:28.263977
...
14782	FTL	trip-153861004148234782	2018-10-03 23:40:41.482736
14783	FTL	trip-153861007249500192	2018-10-03 23:41:12.495257
14784	FTL	trip-153861014185597051	2018-10-03 23:42:21.856227
14785	FTL	trip-153861023893369544	2018-10-03 23:43:58.933947
14786	FTL	trip-153861118270144424	2018-10-03 23:59:42.701692

	source_center	source_name
destination_center \		
0	IND561203AAB	Doddablpur_ChikaDPP_D (Karnataka)
	IND561203AAB	
1	IND400072AAB	Mumbai Hub (Maharashtra)
	IND401104AAA	
2	IND600056AAA	Chennai_Poonamallee (Tamil Nadu)
	IND600056AAA	
3	IND600044AAD	Chennai_Chrompet_DPC (Tamil Nadu)
	IND600048AAA	
4	IND560043AAC	HBR Layout PC (Karnataka)
	IND560043AAC	
...
...		
14782	IND814101AAB	Dumka_Dudhani_D (Jharkhand)
	IND815351AAA	
14783	IND842001AAA	Muzaffrpur_Bbganj_I (Bihar)
	IND842001AAA	
14784	IND206001AAA	Etawah_MhraChng_D (Uttar Pradesh)
	IND209304AAA	
14785	IND382715AAA	Kadi_KaranNGR_D (Gujarat)
	IND382715AAA	
14786	IND583119AAA	Sandur_WrdN1DPP_D (Karnataka)

IND583119AAA

		destination_name	od_start_time	
\				
0		Doddablpur_ChikaDPP_D (Karnataka)	2018-09-12	02:03:09.655591
1		Mumbai_MiraRd_IP (Maharashtra)	2018-09-12	00:01:00.113710
2		Chennai_Poonamallee (Tamil Nadu)	2018-09-12	02:12:10.755603
3		Chennai_Vandalur_Dc (Tamil Nadu)	2018-09-12	00:04:22.011653
4		HBR Layout PC (Karnataka)	2018-09-12	00:04:28.263977
...	

14782		Jamtara_D (Jharkhand)	2018-10-04	04:22:21.025250
14783		Muzaffrpur_Bbganj_I (Bihar)	2018-10-03	23:41:12.495257
14784		Kanpur_Central_H_6 (Uttar Pradesh)	2018-10-05	02:44:50.858859
14785		Kadi_KaranNGR_D (Gujarat)	2018-10-04	01:48:54.382343
14786		Sandur_WrdN1DPP_D (Karnataka)	2018-10-04	03:58:40.726547

		od_end_time	cutoff_factor	\
0		2018-09-12 02:03:09.655591	72	
1		2018-09-12 01:41:29.809822	17	
2		2018-09-12 02:12:10.755603	24	
3		2018-09-12 01:42:22.349694	9	
4		2018-09-12 03:00:55.163423	22	
...		
14782		2018-10-04 02:24:41.382263	167	
14783		2018-10-04 16:40:41.713085	192	
14784		2018-10-04 19:57:34.928573	835	
14785		2018-10-04 01:48:54.382343	84	
14786		2018-10-04 03:58:40.726547	65	

		actual_distance_to_destination	osrm_distance
start_scan_to_end_scan	\		
0		73.186911	85.1110
180.0			
1		17.175274	19.6800
100.0			
2		24.597048	28.0647
189.0			
3		9.100510	12.0184
98.0			
4		22.424210	28.9203

146.0		
...
...		
14782	168.396341	207.4975
428.0		
14783	194.552260	229.2052
1017.0		
14784	836.072017	997.7577
2180.0		
14785	84.743813	102.3828
256.0		
14786	66.081533	80.5787
353.0		

	segment_actual_time	segment_osrm_time	actual_time	osrm_time
\				
0	141.0	65.0	143.0	68.0
1	59.0	16.0	59.0	15.0
2	60.0	23.0	61.0	23.0
3	24.0	13.0	24.0	13.0
4	64.0	34.0	64.0	34.0
...
14782	347.0	220.0	349.0	220.0
14783	845.0	178.0	847.0	178.0
14784	1660.0	891.0	1674.0	724.0
14785	186.0	92.0	187.0	92.0
14786	274.0	67.0	275.0	68.0

	segment_osrm_distance
0	84.1894
1	19.8766
2	28.0647
3	12.0184
4	28.9203
...	...
14782	209.4499
14783	232.5811
14784	1166.3614
14785	107.6915

```
14786          80.5787
```

```
[14787 rows x 18 columns]
```

```
data.nunique() # Unique values in the dataset
```

```
route_type          2
trip_uuid           14787
trip_creation_time   14787
source_center        930
source_name          930
destination_center   1035
destination_name     1035
od_start_time        14787
od_end_time          14787
cutoff_factor        684
actual_distance_to_destination 14771
osrm_distance        14706
start_scan_to_end_scan 2203
segment_actual_time  1887
segment_osrm_time    1242
actual_time          1850
osrm_time            827
segment_osrm_distance 14724
dtype: int64
```

```
data.isna().sum() #nullvalues in the data frame
```

```
route_type          0
trip_uuid           0
trip_creation_time   0
source_center        0
source_name          0
destination_center   0
destination_name     0
od_start_time        0
od_end_time          0
cutoff_factor        0
actual_distance_to_destination 0
osrm_distance        0
start_scan_to_end_scan 0
segment_actual_time  0
segment_osrm_time    0
actual_time          0
osrm_time            0
segment_osrm_distance 0
dtype: int64
```

```
data.describe() #statistical summary of dataset
```

	cutoff_factor	actual_distance_to_destination	osrm_distance	\
count	14787.000000	14787.000000	14787.000000	
mean	163.379523	164.290730	204.631953	
std	305.558531	305.678137	370.953239	
min	9.000000	9.002461	9.072900	
25%	22.000000	22.840056	30.875600	
50%	48.000000	48.376934	65.575600	
75%	162.000000	163.685113	207.087600	
max	2185.000000	2187.483994	2840.081000	

	start_scan_to_end_scan	segment_actual_time	segment_osrm_time
\			
count	14787.000000	14787.000000	14787.000000
mean	529.442754	353.118618	180.482924
std	658.286556	556.439155	314.622727
min	23.000000	9.000000	6.000000
25%	149.000000	66.000000	30.000000
50%	279.000000	147.000000	65.000000
75%	632.000000	364.000000	184.000000
max	7898.000000	6230.000000	2564.000000

	actual_time	osrm_time	segment_osrm_distance
count	14787.000000	14787.000000	14787.000000
mean	356.316224	161.667072	222.66823
std	561.528033	272.406218	416.76499
min	9.000000	6.000000	9.07290
25%	67.000000	29.000000	32.57885
50%	148.000000	60.000000	69.78420
75%	367.000000	168.000000	216.46395
max	6265.000000	2032.000000	3523.63240

data.describe(include=object)

	route_type	trip_uuid	trip_creation_time
\			
count	14787	14787	14787
unique	2	14787	14787
top	Carting	trip-153671042288605164	2018-09-12 00:00:22.886430
freq	8906	1	1

	source_center	source_name	destination_center
\			
count	14787	14787	14787
unique	930	930	1035
top	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)	IND000000ACB
freq	1052	1052	821

	destination_name	od_start_time	\
count	14787	14787	
unique	1035	14787	
top	Gurgaon_Bilaspur_HB (Haryana)	2018-09-12 02:03:09.655591	
freq	821	1	

	od_end_time
count	14787
unique	14787
top	2018-09-12 02:03:09.655591
freq	1

Feature Generation

```
#Feature generation like source_state and destination_state
data["source_state"]=data["source_name"].apply(lambda x:
str(x).split("(")[1][:-1])
data["destination_state"]=data["destination_name"].apply(lambda x:
str(x).split("(")[1][:-1])
data
```

	route_type	trip_uuid	trip_creation_time
\			
0	Carting	trip-153671042288605164	2018-09-12 00:00:22.886430
1	Carting	trip-153671046011330457	2018-09-12 00:01:00.113710
2	Carting	trip-153671055416136166	2018-09-12 00:02:34.161600
3	Carting	trip-153671066201138152	2018-09-12 00:04:22.011653
4	Carting	trip-153671066826362165	2018-09-12 00:04:28.263977
...
14782	FTL	trip-153861004148234782	2018-10-03 23:40:41.482736

14783	FTL	trip-153861007249500192	2018-10-03	23:41:12.495257
14784	FTL	trip-153861014185597051	2018-10-03	23:42:21.856227
14785	FTL	trip-153861023893369544	2018-10-03	23:43:58.933947
14786	FTL	trip-153861118270144424	2018-10-03	23:59:42.701692

	source_center	source_name
destination_center \		
0	IND561203AAB	Doddablpur_ChikaDPP_D (Karnataka)
	IND561203AAB	
1	IND400072AAB	Mumbai Hub (Maharashtra)
	IND401104AAA	
2	IND600056AAA	Chennai_Poonamallee (Tamil Nadu)
	IND600056AAA	
3	IND600044AAD	Chennai_Chrompet_DPC (Tamil Nadu)
	IND600048AAA	
4	IND560043AAC	HBR Layout PC (Karnataka)
	IND560043AAC	
...
...		
14782	IND814101AAB	Dumka_Dudhani_D (Jharkhand)
	IND815351AAA	
14783	IND842001AAA	Muzaffrpur_Bbganj_I (Bihar)
	IND842001AAA	
14784	IND206001AAA	Etawah_MhraChng_D (Uttar Pradesh)
	IND209304AAA	
14785	IND382715AAA	Kadi_KaranNGR_D (Gujarat)
	IND382715AAA	
14786	IND583119AAA	Sandur_WrdN1DPP_D (Karnataka)
	IND583119AAA	

	destination_name	od_start_time
\		
0	Doddablpur_ChikaDPP_D (Karnataka)	2018-09-12 02:03:09.655591
1	Mumbai_MiraRd_IP (Maharashtra)	2018-09-12 00:01:00.113710
2	Chennai_Poonamallee (Tamil Nadu)	2018-09-12 02:12:10.755603
3	Chennai_Vandalur_Dc (Tamil Nadu)	2018-09-12 00:04:22.011653
4	HBR Layout PC (Karnataka)	2018-09-12 00:04:28.263977
...
14782	Jamtara_D (Jharkhand)	2018-10-04 04:22:21.025250

14783	Muzaffrpur_Bbganj_I (Bihar)	2018-10-03	23:41:12.495257
14784	Kanpur_Central_H_6 (Uttar Pradesh)	2018-10-05	02:44:50.858859
14785	Kadi_KaranNGR_D (Gujarat)	2018-10-04	01:48:54.382343
14786	Sandur_WrdN1DPP_D (Karnataka)	2018-10-04	03:58:40.726547

	od_end_time	cutoff_factor	\
0	2018-09-12 02:03:09.655591	72	
1	2018-09-12 01:41:29.809822	17	
2	2018-09-12 02:12:10.755603	24	
3	2018-09-12 01:42:22.349694	9	
4	2018-09-12 03:00:55.163423	22	
...	
14782	2018-10-04 02:24:41.382263	167	
14783	2018-10-04 16:40:41.713085	192	
14784	2018-10-04 19:57:34.928573	835	
14785	2018-10-04 01:48:54.382343	84	
14786	2018-10-04 03:58:40.726547	65	

	actual_distance_to_destination	osrm_distance
start_scan_to_end_scan \		
0	73.186911	85.1110
180.0		
1	17.175274	19.6800
100.0		
2	24.597048	28.0647
189.0		
3	9.100510	12.0184
98.0		
4	22.424210	28.9203
146.0		
...
...		
14782	168.396341	207.4975
428.0		
14783	194.552260	229.2052
1017.0		
14784	836.072017	997.7577
2180.0		
14785	84.743813	102.3828
256.0		
14786	66.081533	80.5787
353.0		

	segment_actual_time	segment_osrm_time	actual_time	osrm_time
\				
0	141.0	65.0	143.0	68.0

1	59.0	16.0	59.0	15.0
2	60.0	23.0	61.0	23.0
3	24.0	13.0	24.0	13.0
4	64.0	34.0	64.0	34.0
...
14782	347.0	220.0	349.0	220.0
14783	845.0	178.0	847.0	178.0
14784	1660.0	891.0	1674.0	724.0
14785	186.0	92.0	187.0	92.0
14786	274.0	67.0	275.0	68.0

	segment_osrm_distance	source_state	destination_state
0	84.1894	Karnataka	Karnataka
1	19.8766	Maharashtra	Maharashtra
2	28.0647	Tamil Nadu	Tamil Nadu
3	12.0184	Tamil Nadu	Tamil Nadu
4	28.9203	Karnataka	Karnataka
...
14782	209.4499	Jharkhand	Jharkhand
14783	232.5811	Bihar	Bihar
14784	1166.3614	Uttar Pradesh	Uttar Pradesh
14785	107.6915	Gujarat	Gujarat
14786	80.5787	Karnataka	Karnataka

```
[14787 rows x 20 columns]
```

```
data.describe(include=object)
```

	route_type	trip_uuid	trip_creation_time
\count	14787	14787	14787
unique	2	14787	14787
top	Carting	trip-153671042288605164	2018-09-12 00:00:22.886430
freq	8906	1	1
	source center	source name	destination center

\	count	14787	14787	14787
	unique	930	930	1035
top	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)	IND000000ACB	
	freq	1052	1052	821

	destination_name	od_start_time	\
count	14787	14787	
unique	1035	14787	
top	Gurgaon_Bilaspur_HB (Haryana)	2018-09-12 02:03:09.655591	
freq	821	1	

	od_end_time	source_state	destination_state
count	14787	14787	14787
unique	14787	29	31
top	2018-09-12 02:03:09.655591	Maharashtra	Maharashtra
freq	1	2714	2561

data.nunique() *#unique value in dataframe*

route_type	2
trip_uuid	14787
trip_creation_time	14787
source_center	930
source_name	930
destination_center	1035
destination_name	1035
od_start_time	14787
od_end_time	14787
cutoff_factor	684
actual_distance_to_destination	14771
osrm_distance	14706
start_scan_to_end_scan	2203
segment_actual_time	1887
segment_osrm_time	1242
actual_time	1850
osrm_time	827
segment_osrm_distance	14724
source_state	29
destination_state	31
dtype:	int64

data["source_state"].value_counts() *#source-statewise trip count*

Maharashtra	2714
Karnataka	2143
Haryana	1823

Tamil Nadu	1039
Telangana	784
Uttar Pradesh	760
Gujarat	750
Delhi	725
West Bengal	665
Punjab	536
Rajasthan	514
Andhra Pradesh	435
Bihar	351
Madhya Pradesh	318
Kerala	289
Assam	268
Jharkhand	160
Uttarakhand	114
Orissa	107
Chandigarh	93
Goa	65
Chhattisgarh	43
Himachal Pradesh	34
Jammu & Kashmir	17
Dadra and Nagar Haveli	15
Pondicherry	12
Nagaland	5
Arunachal Pradesh	4
Mizoram	4

Name: source_state, dtype: int64

`data["destination_state"].value_counts()` *#destination-statewise trip count*

Maharashtra	2561
Karnataka	2294
Haryana	1640
Tamil Nadu	1084
Uttar Pradesh	805
Telangana	784
Gujarat	734
West Bengal	697
Delhi	657
Punjab	617
Rajasthan	550
Andhra Pradesh	442
Bihar	367
Madhya Pradesh	350
Kerala	270
Assam	232
Jharkhand	181
Uttarakhand	122
Orissa	119

Chandigarh	65
Goa	52
Chhattisgarh	43
Himachal Pradesh	42
Arunachal Pradesh	25
Jammu & Kashmir	20
Dadra and Nagar Haveli	17
Meghalaya	8
Mizoram	6
Nagaland	1
Daman & Diu	1
Tripura	1

Name: destination_state, dtype: int64

```
data["source_name"].value_counts().head()
```

Gurgaon_Bilaspur_HB (Haryana)	1052
Bhiwandi_Mankoli_HB (Maharashtra)	697
Bangalore_Nelmngla_H (Karnataka)	624
Bengaluru_Bomsndra_HB (Karnataka)	455
Pune_Tathawde_H (Maharashtra)	396

Name: source_name, dtype: int64

```
data["source_name"].value_counts().tail()
```

Chikodi_IndraNgr_D (Karnataka)	1
Atmakur_IndraNgr_D (Andhra Pradesh)	1
Jetpur_DC (Gujarat)	1
Bantwal_Trmltmpl_D (Karnataka)	1
Sandur_WrdN1DPP_D (Karnataka)	1

Name: source_name, dtype: int64

```
data["destination_name"].value_counts().head()
```

Gurgaon_Bilaspur_HB (Haryana)	821
Bangalore_Nelmngla_H (Karnataka)	548
Bhiwandi_Mankoli_HB (Maharashtra)	403
Bengaluru_Bomsndra_HB (Karnataka)	342
Hyderabad_Shamshbd_H (Telangana)	280

Name: destination_name, dtype: int64

```
data["source-destination"]=data["source_name"] +  
data["destination_name"]
```

```
data["source-destination"].value_counts() #Busiest Corridors
```

Bangalore_Nelmngla_H (Karnataka)Bengaluru_KGAirprt_HB (Karnataka)	151
Gurgaon_Bilaspur_HB (Haryana)Gurgaon_Bilaspur_HB (Haryana)	123
Bengaluru_Bomsndra_HB (Karnataka)Bengaluru_KGAirprt_HB (Karnataka)	

```

121
Bengaluru_KGAirprt_HB (Karnataka)Bangalore_Nelmngla_H (Karnataka)
108
Bhiwandi_Mankoli_HB (Maharashtra)Mumbai Hub (Maharashtra)
105
...
Khammam_NSTRoad_I (Telangana)Nalgonda_HydRoad_DC (Telangana)
1
Kolkata_Dankuni_HB (West Bengal)Tarkeshwar_Naraynpr_D (West Bengal)
1
Bamangola_Central_D_1 (West Bengal)Malda_krshnPly_DC (West Bengal)
1
Nalbari_Bhgtpura_D (Assam)Dhubri_Tetultol_D (Assam)
1
Sandur_WrdN1DPP_D (Karnataka)Sandur_WrdN1DPP_D (Karnataka)
1
Name: source-destination, Length: 2165, dtype: int64

#Average distance
data[data["source-destination"]=="Bangalore_Nelmngla_H
(Karnataka)Bengaluru_KGAirprt_HB (Karnataka)"]
["actual_distance_to_destination"].mean()

28.03163476896394

#Average time
data[data["source-destination"]=="Bangalore_Nelmngla_H
(Karnataka)Bengaluru_KGAirprt_HB (Karnataka)"]["actual_time"].mean()

87.87417218543047

data.drop("source-destination",axis=1,inplace=True)

data["trip_creation_time"]=pd.to_datetime(df["trip_creation_time"]) #
conversion to datetime datatype

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14787 entries, 0 to 14786
Data columns (total 20 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   route_type                            14787 non-null   object
1   trip_uuid                             14787 non-null   object
2   trip_creation_time                    14783 non-null   datetime64[ns]
3   source_center                         14787 non-null   object
4   source_name                           14787 non-null   object
5   destination_center                    14787 non-null   object
6   destination_name                      14787 non-null   object

```

```

7    od_start_time          14787 non-null object
8    od_end_time            14787 non-null object
9    cutoff_factor          14787 non-null int64
10   actual_distance_to_destination 14787 non-null float64
11   osrm_distance          14787 non-null float64
12   start_scan_to_end_scan 14787 non-null float64
13   segment_actual_time    14787 non-null float64
14   segment_osrm_time      14787 non-null float64
15   actual_time            14787 non-null float64
16   osrm_time              14787 non-null float64
17   segment_osrm_distance  14787 non-null float64
18   source_state           14787 non-null object
19   destination_state       14787 non-null object
dtypes: datetime64[ns](1), float64(8), int64(1), object(10)
memory usage: 2.3+ MB

```

#Feature generation year

```

data["trip_creation_year"]=data["trip_creation_time"].dt.year
data["trip_creation_year"].value_counts()

```

```

2018.0    14783
Name: trip_creation_year, dtype: int64

```

#Feature generation month

```

data["trip_creation_month"]=data["trip_creation_time"].dt.month
data["trip_creation_month"].value_counts()

```

```

9.0    13092
10.0    1691
Name: trip_creation_month, dtype: int64

```

#Feature generation day

```

data["trip_creation_day"]=data["trip_creation_time"].dt.day
data["trip_creation_day"].value_counts()

```

```

25.0    1024
17.0    1000
20.0     854
23.0     820
15.0     809
12.0     779
14.0     762
28.0     731
3.0      695
24.0     674
16.0     657
21.0     657
26.0     642
18.0     580
19.0     571
30.0     552

```



```
22.0    544
1.0     539
13.0    516
29.0    463
27.0    457
2.0     457
```

```
Name: trip_creation_day, dtype: int64
```

#Feature generation triptime

```
data["od_start_time"]=pd.to_datetime(data["od_start_time"])
data["od_end_time"]=pd.to_datetime(data["od_end_time"])
data["trip_time"]=data["od_end_time"]-data["od_start_time"]
data
```

	route_type	trip_uuid
trip_creation_time \		
0	Carting	trip-153671042288605164 2018-09-20 02:35:36.476840
1	Carting	trip-153671046011330457 2018-09-20 02:35:36.476840
2	Carting	trip-153671055416136166 2018-09-20 02:35:36.476840
3	Carting	trip-153671066201138152 2018-09-20 02:35:36.476840
4	Carting	trip-153671066826362165 2018-09-20 02:35:36.476840
...
14782	FTL	trip-153861004148234782 2018-09-24 05:06:56.558662
14783	FTL	trip-153861007249500192 2018-09-24 05:06:56.558662
14784	FTL	trip-153861014185597051 2018-09-24 05:06:56.558662
14785	FTL	trip-153861023893369544 2018-09-24 05:06:56.558662
14786	FTL	trip-153861118270144424 2018-09-24 05:06:56.558662

	source_center	source_name
destination_center \		
0	IND561203AAB	Doddablpur_ChikaDPP_D (Karnataka)
IND561203AAB		
1	IND400072AAB	Mumbai Hub (Maharashtra)
IND401104AAA		
2	IND600056AAA	Chennai_Poonamallee (Tamil Nadu)
IND600056AAA		
3	IND600044AAD	Chennai_Chrompet_DPC (Tamil Nadu)
IND600048AAA		
4	IND560043AAC	HBR Layout PC (Karnataka)
IND560043AAC		

```

...
...
14782 IND814101AAB Dumka_Dudhani_D (Jharkhand)
IND815351AAA
14783 IND842001AAA Muzaffrpur_Bbganj_I (Bihar)
IND842001AAA
14784 IND206001AAA Etawah_MhraChng_D (Uttar Pradesh)
IND209304AAA
14785 IND382715AAA Kadi_KaranNGR_D (Gujarat)
IND382715AAA
14786 IND583119AAA Sandur_WrdN1DPP_D (Karnataka)
IND583119AAA

destination_name
od_start_time \
0 Doddablpur_ChikaDPP_D (Karnataka) 2018-09-12 02:03:09.655591
1 Mumbai_MiraRd_IP (Maharashtra) 2018-09-12 00:01:00.113710
2 Chennai_Poonamallee (Tamil Nadu) 2018-09-12 02:12:10.755603
3 Chennai_Vandalur_Dc (Tamil Nadu) 2018-09-12 00:04:22.011653
4 HBR Layout PC (Karnataka) 2018-09-12 00:04:28.263977
...
...
14782 Jamtara_D (Jharkhand) 2018-10-04 04:22:21.025250
14783 Muzaffrpur_Bbganj_I (Bihar) 2018-10-03 23:41:12.495257
14784 Kanpur_Central_H_6 (Uttar Pradesh) 2018-10-05 02:44:50.858859
14785 Kadi_KaranNGR_D (Gujarat) 2018-10-04 01:48:54.382343
14786 Sandur_WrdN1DPP_D (Karnataka) 2018-10-04 03:58:40.726547

od_end_time cutoff_factor ...
segment_osrm_time \
0 2018-09-12 02:03:09.655591 72 ...
65.0
1 2018-09-12 01:41:29.809822 17 ...
16.0
2 2018-09-12 02:12:10.755603 24 ...
23.0
3 2018-09-12 01:42:22.349694 9 ...
13.0
4 2018-09-12 03:00:55.163423 22 ...
34.0

```

```

...
.
14782 2018-10-04 02:24:41.382263 167 ...
220.0
14783 2018-10-04 16:40:41.713085 192 ...
178.0
14784 2018-10-04 19:57:34.928573 835 ...
891.0
14785 2018-10-04 01:48:54.382343 84 ...
92.0
14786 2018-10-04 03:58:40.726547 65 ...
67.0

```

	actual_time	osrm_time	segment_osrm_distance	source_state \
0	143.0	68.0	84.1894	Karnataka
1	59.0	15.0	19.8766	Maharashtra
2	61.0	23.0	28.0647	Tamil Nadu
3	24.0	13.0	12.0184	Tamil Nadu
4	64.0	34.0	28.9203	Karnataka
...
14782	349.0	220.0	209.4499	Jharkhand
14783	847.0	178.0	232.5811	Bihar
14784	1674.0	724.0	1166.3614	Uttar Pradesh
14785	187.0	92.0	107.6915	Gujarat
14786	275.0	68.0	80.5787	Karnataka

	destination_state	trip_creation_year	trip_creation_month \
0	Karnataka	2018.0	9.0
1	Maharashtra	2018.0	9.0
2	Tamil Nadu	2018.0	9.0
3	Tamil Nadu	2018.0	9.0
4	Karnataka	2018.0	9.0
...
14782	Jharkhand	2018.0	9.0
14783	Bihar	2018.0	9.0
14784	Uttar Pradesh	2018.0	9.0
14785	Gujarat	2018.0	9.0
14786	Karnataka	2018.0	9.0

	trip_creation_day	trip_time
0	20.0	0 days 00:00:00
1	20.0	0 days 01:40:29.696112
2	20.0	0 days 00:00:00
3	20.0	0 days 01:38:00.338041
4	20.0	0 days 02:56:26.899446
...
14782	24.0	-1 days +22:02:20.357013
14783	24.0	0 days 16:59:29.217828
14784	24.0	-1 days +17:12:44.069714
14785	24.0	0 days 00:00:00

```
14786          24.0          0 days 00:00:00
```

```
[14787 rows x 24 columns]
```

```
data.isnull().sum()
```

route_type	0
trip_uuid	0
trip_creation_time	4
source_center	0
source_name	0
destination_center	0
destination_name	0
od_start_time	0
od_end_time	0
cutoff_factor	0
actual_distance_to_destination	0
osrm_distance	0
start_scan_to_end_scan	0
segment_actual_time	0
segment_osrm_time	0
actual_time	0
osrm_time	0
segment_osrm_distance	0
source_state	0
destination_state	0
trip_creation_year	4
trip_creation_month	4
trip_creation_day	4
trip_time	0
dtype: int64	

```
data.dropna(inplace=True)
```

```
data.isnull().sum()
```

route_type	0
trip_uuid	0
trip_creation_time	0
source_center	0
source_name	0
destination_center	0
destination_name	0
od_start_time	0
od_end_time	0
cutoff_factor	0
actual_distance_to_destination	0
osrm_distance	0
start_scan_to_end_scan	0
segment_actual_time	0

```

segment_osrm_time      0
actual_time            0
osrm_time              0
segment_osrm_distance  0
source_state           0
destination_state      0
trip_creation_year     0
trip_creation_month    0
trip_creation_day      0
trip_time              0
dtype: int64

```

```
data.shape
```

```
(14783, 24)
```

```
#conversion of triptime to float type data
```

```
data["triptime_sec"]=data["trip_time"].dt.total_seconds()
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 14783 entries, 0 to 14786
```

```
Data columns (total 25 columns):
```

#	Column	Non-Null Count	Dtype
0	route_type	14783 non-null	object
1	trip_uuid	14783 non-null	object
2	trip_creation_time	14783 non-null	datetime64[ns]
3	source_center	14783 non-null	object
4	source_name	14783 non-null	object
5	destination_center	14783 non-null	object
6	destination_name	14783 non-null	object
7	od_start_time	14783 non-null	datetime64[ns]
8	od_end_time	14783 non-null	datetime64[ns]
9	cutoff_factor	14783 non-null	int64
10	actual_distance_to_destination	14783 non-null	float64
11	osrm_distance	14783 non-null	float64
12	start_scan_to_end_scan	14783 non-null	float64
13	segment_actual_time	14783 non-null	float64
14	segment_osrm_time	14783 non-null	float64
15	actual_time	14783 non-null	float64
16	osrm_time	14783 non-null	float64
17	segment_osrm_distance	14783 non-null	float64
18	source_state	14783 non-null	object
19	destination_state	14783 non-null	object
20	trip_creation_year	14783 non-null	float64
21	trip_creation_month	14783 non-null	float64
22	trip_creation_day	14783 non-null	float64
23	trip_time	14783 non-null	timedelta64[ns]

```
24 triptime_sec          14783 non-null float64
dtypes: datetime64[ns](3), float64(12), int64(1), object(8),
timedelta64[ns](1)
memory usage: 2.9+ MB
```

```
data[data["triptime_sec"]<0]
```

	route_type	trip_creation_time \	trip_uuid
5	Carting	trip-153671074033284934	2018-09-20 02:35:36.476840
14	Carting	trip-153671202698783427	2018-09-23 06:42:06.021680
16	Carting	trip-153671225291120891	2018-09-14 15:42:46.437249
31	Carting	trip-153671440490445199	2018-09-13 20:44:19.424489
35	Carting	trip-153671508851597828	2018-09-29 22:21:45.149226
...
14768	FTL	trip-153860767482259863	2018-09-24 05:06:56.558662
14779	FTL	trip-153860945742225615	2018-09-24 05:06:56.558662
14781	FTL	trip-153860985527721606	2018-09-24 05:06:56.558662
14782	FTL	trip-153861004148234782	2018-09-24 05:06:56.558662
14784	FTL	trip-153861014185597051	2018-09-24 05:06:56.558662

	source_center	source_name
5	IND395009AAA	Surat_Central_D_12 (Gujarat)
	IND395004AAB	
14	IND395001AAA	Surat_Central_D_9 (Gujarat)
	IND395006AAA	
16	IND712103AAA	Hoogly_Bandel_D (West Bengal)
	IND712124AAA	
31	IND140501AAA	Lalru_OnkarDPP_D (Punjab)
	IND134203AAA	
35	IND360530AAB	Jamjodhpur_Court_D (Gujarat)
	IND360575AAA	
...
...		
14768	IND505122AAA	Jammikunta_ConduDPP_D (Telangana)
	IND505467AAA	
14779	IND140001AAA	RoopNagar_ChotiHvl_DC (Punjab)
	IND140301AAA	
14781	IND814133AAB	Godda_Central_D_2 (Jharkhand)

IND815301AAA

14782 IND814101AAB Dumka_Dudhani_D (Jharkhand)

IND815351AAA

14784 IND206001AAA Etawah_MhraChng_D (Uttar Pradesh)

IND209304AAA

	destination_name			
od_start_time \				
5	Surat_Central_D_3 (Gujarat)	2018-09-12	02:31:39.246238	
14	Surat_Varachha_DC (Gujarat)	2018-09-12	02:37:19.832796	
16	Hooghly_DC (West Bengal)	2018-09-12	03:09:08.473151	
31	Naraingarh_Ward2DPP_D (Haryana)	2018-09-12	07:36:00.152620	
35	Porbandar_DC (Gujarat)	2018-09-12	06:04:58.698852	
...	
14768	Husnabad_Greenmkt_D (Telangana)	2018-10-04	03:51:10.928009	
14779	Chandigarh_Kharar_DC (Chandigarh)	2018-10-04	03:46:12.300247	
14781	Giridih_Shivalya_D (Jharkhand)	2018-10-04	08:29:20.440999	
14782	Jamtara_D (Jharkhand)	2018-10-04	04:22:21.025250	
14784	Kanpur_Central_H_6 (Uttar Pradesh)	2018-10-05	02:44:50.858859	

	od_end_time	cutoff_factor	...	actual_time
osrm_time \				
5	2018-09-12 02:01:41.638015	25	...	161.0
29.0				
14	2018-09-12 02:04:22.360575	19	...	170.0
29.0				
16	2018-09-12 02:16:17.710493	51	...	222.0
58.0				
31	2018-09-12 03:55:15.023521	47	...	147.0
64.0				
35	2018-09-12 03:43:56.169739	178	...	553.0
192.0				
...
...				
14768	2018-10-04 02:25:04.243970	104	...	380.0
119.0				
14779	2018-10-04 02:52:02.434753	183	...	281.0
207.0				
14781	2018-10-04 03:01:57.954149	226	...	511.0

```

248.0
14782 2018-10-04 02:24:41.382263          167 ...          349.0
220.0
14784 2018-10-04 19:57:34.928573          835 ...          1674.0
724.0

```

	segment_osrm_distance	source_state	destination_state	\
5	30.9358	Gujarat	Gujarat	
14	30.5457	Gujarat	Gujarat	
16	71.3328	West Bengal	West Bengal	
31	103.6903	Punjab	Haryana	
35	245.2043	Gujarat	Gujarat	
...	
14768	140.2444	Telangana	Telangana	
14779	216.3882	Punjab	Chandigarh	
14781	378.6774	Jharkhand	Jharkhand	
14782	209.4499	Jharkhand	Jharkhand	
14784	1166.3614	Uttar Pradesh	Uttar Pradesh	

	trip_creation_year	trip_creation_month	trip_creation_day	\
5	2018.0	9.0	20.0	
14	2018.0	9.0	23.0	
16	2018.0	9.0	14.0	
31	2018.0	9.0	13.0	
35	2018.0	9.0	29.0	
...	
14768	2018.0	9.0	24.0	
14779	2018.0	9.0	24.0	
14781	2018.0	9.0	24.0	
14782	2018.0	9.0	24.0	
14784	2018.0	9.0	24.0	

	trip_time	triptime_sec
5	-1 days +23:30:02.391777	-1797.608223
14	-1 days +23:27:02.527779	-1977.472221
16	-1 days +23:07:09.237342	-3170.762658
31	-1 days +20:19:14.870901	-13245.129099
35	-1 days +21:38:57.470887	-8462.529113
...
14768	-1 days +22:33:53.315961	-5166.684039
14779	-1 days +23:05:50.134506	-3249.865494
14781	-1 days +18:32:37.513150	-19642.486850
14782	-1 days +22:02:20.357013	-7059.642987
14784	-1 days +17:12:44.069714	-24435.930286

```
[891 rows x 25 columns]
```

```

#Here Triptime can not be negative values as travelling time should
always be positive, so we will drop that rows as its false values
data.drop(data[data["triptime_sec"]<0].index,inplace=True)

```



```
data.describe()
```

	cutoff_factor	actual_distance_to_destination	osrm_distance \
count	13892.000000	13892.000000	13892.000000
mean	159.986251	160.852618	200.437664
std	307.520122	307.627703	373.619022
min	9.000000	9.002461	9.072900
25%	21.000000	22.037144	29.802900
50%	46.000000	46.163919	61.108100
75%	148.000000	149.281573	193.689125
max	2185.000000	2187.483994	2840.081000

	start_scan_to_end_scan	segment_actual_time	segment_osrm_time
count	13892.000000	13892.000000	13892.000000
mean	515.603657	346.118557	176.627627
std	660.357703	561.918712	316.580388
min	23.000000	9.000000	6.000000
25%	144.000000	64.000000	30.000000
50%	264.000000	136.000000	62.000000
75%	595.000000	349.000000	176.000000
max	7898.000000	6230.000000	2564.000000

	actual_time	osrm_time	segment_osrm_distance
trip_creation_year \			
count	13892.000000	13892.000000	13892.000000
13892.0			
mean	349.267492	157.980564	218.437771
2018.0			
std	567.051777	274.050917	419.933226
0.0			
min	9.000000	6.000000	9.072900
2018.0			
25%	65.000000	29.000000	31.349950
2018.0			
50%	138.000000	57.500000	65.614850
2018.0			
75%	353.000000	163.250000	204.588700
2018.0			
max	6265.000000	2032.000000	3523.632400
2018.0			

trip_creation_month	trip_creation_day
---------------------	-------------------

trip_time \			
count	13892.000000	13892.000000	
13892			
mean	9.114310	18.547653	0 days
06:45:04.119232843			
std	0.318199	7.753191	0 days
09:33:47.061593031			
min	9.000000	1.000000	0 days
00:00:00			
25%	9.000000	14.000000	0 days
01:51:56.299656750			
50%	9.000000	20.000000	0 days
03:30:54.417636			
75%	9.000000	25.000000	0 days
07:04:21.465968500			
max	10.000000	30.000000	5 days
11:38:33.117274			

	triptime_sec
count	13892.000000
mean	24304.119233
std	34427.061593
min	0.000000
25%	6716.299657
50%	12654.417636
75%	25461.465969
max	473913.117274

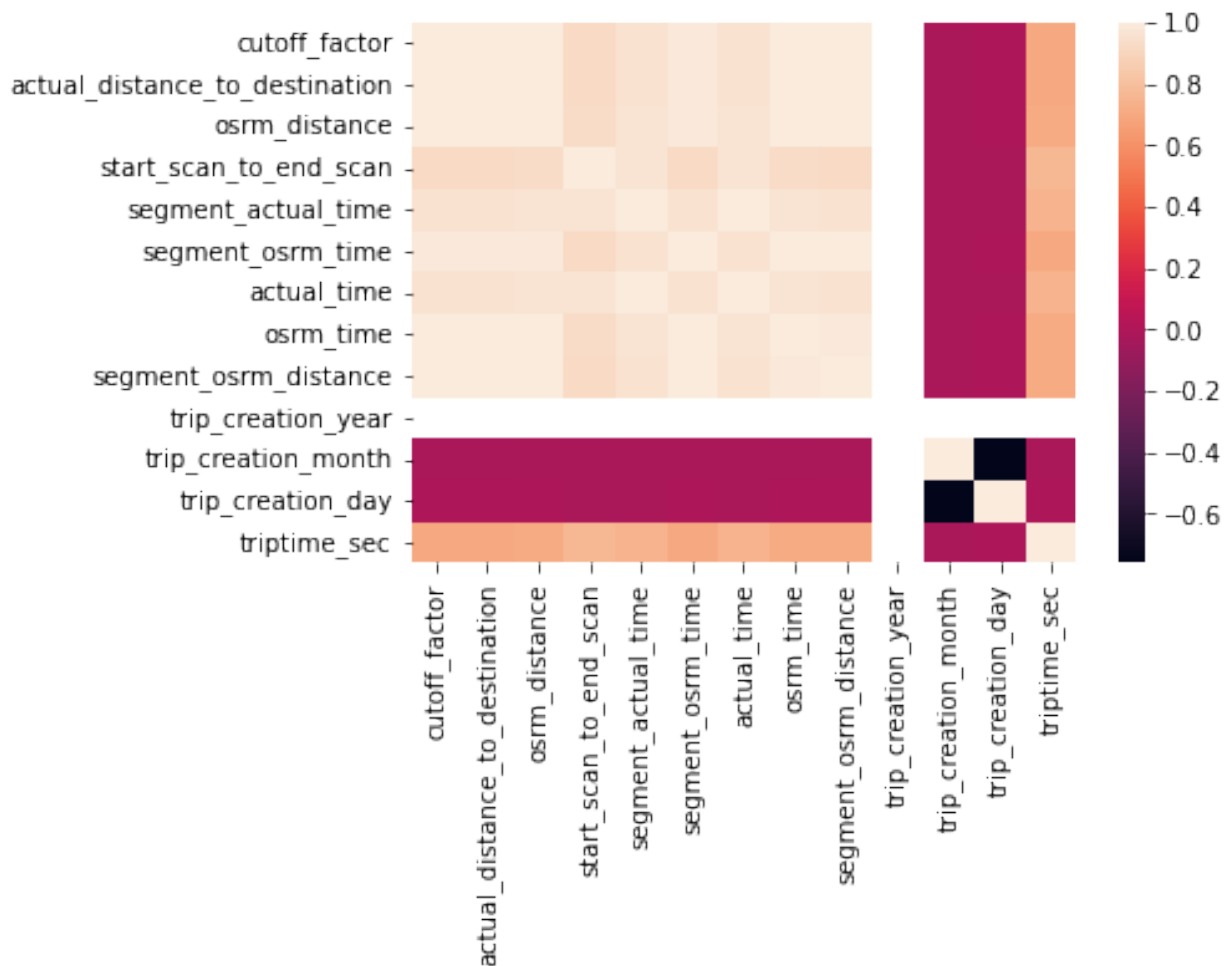
#Heatmap of dataframe

```
sns.heatmap(data.corr())
```

C:\Users\Pipaliya\AppData\Local\Temp\ipykernel_8836\1199273054.py:2:
FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

```
sns.heatmap(data.corr())
```

<AxesSubplot: >



```
data.corr()
```

```
C:\Users\Pipaliya\AppData\Local\Temp\ipykernel_8836\2627137660.py:1:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only
valid columns or specify the value of numeric_only to silence this
warning.
```

```
data.corr()
```

```

          cutoff_factor
actual_distance_to_destination \
cutoff_factor                1.000000
0.999997
actual_distance_to_destination    0.999997
1.000000
osrm_distance                    0.997444
0.997471
start_scan_to_end_scan          0.921081
0.921345
segment_actual_time             0.954552
```

0.954682		
segment_osrm_time	0.988451	
0.988498		
actual_time	0.955434	
0.955563		
osrm_time	0.994283	
0.994361		
segment_osrm_distance	0.993405	
0.993410		
trip_creation_year	NaN	
NaN		
trip_creation_month	-0.019440	-
0.019482		
trip_creation_day	-0.011132	-
0.011104		
triptime_sec	0.703598	
0.703577		

	osrm_distance	start_scan_to_end_scan
\		
cutoff_factor	0.997444	0.921081
actual_distance_to_destination	0.997471	0.921345
osrm_distance	1.000000	0.927050
start_scan_to_end_scan	0.927050	1.000000
segment_actual_time	0.959676	0.963516
segment_osrm_time	0.992424	0.921375
actual_time	0.960492	0.963525
osrm_time	0.997933	0.929408
segment_osrm_distance	0.995036	0.922120
trip_creation_year	NaN	NaN
trip_creation_month	-0.018993	-0.019450
trip_creation_day	-0.011031	-0.014236
triptime_sec	0.704835	0.765778

	segment_actual_time	segment_osrm_time
\		
cutoff_factor	0.954552	0.988451

actual_distance_to_destination	0.954682	0.988498
osrm_distance	0.959676	0.992424
start_scan_to_end_scan	0.963516	0.921375
segment_actual_time	1.000000	0.954571
segment_osrm_time	0.954571	1.000000
actual_time	0.999978	0.955367
osrm_time	0.959483	0.993647
segment_osrm_distance	0.957497	0.996487
trip_creation_year	NaN	NaN
trip_creation_month	-0.017506	-0.019008
trip_creation_day	-0.013692	-0.010119
triptime_sec	0.745170	0.701954

	actual_time	osrm_time
segment_osrm_distance \		
cutoff_factor	0.955434	0.994283
0.993405		
actual_distance_to_destination	0.955563	0.994361
0.993410		
osrm_distance	0.960492	0.997933
0.995036		
start_scan_to_end_scan	0.963525	0.929408
0.922120		
segment_actual_time	0.999978	0.959483
0.957497		
segment_osrm_time	0.955367	0.993647
0.996487		
actual_time	1.000000	0.960269
0.958320		
osrm_time	0.960269	1.000000
0.992408		
segment_osrm_distance	0.958320	0.992408
1.000000		
trip_creation_year	NaN	NaN
NaN		
trip_creation_month	-0.017533	-0.020042
0.019023		-
trip_creation_day	-0.013676	-0.010269
		-

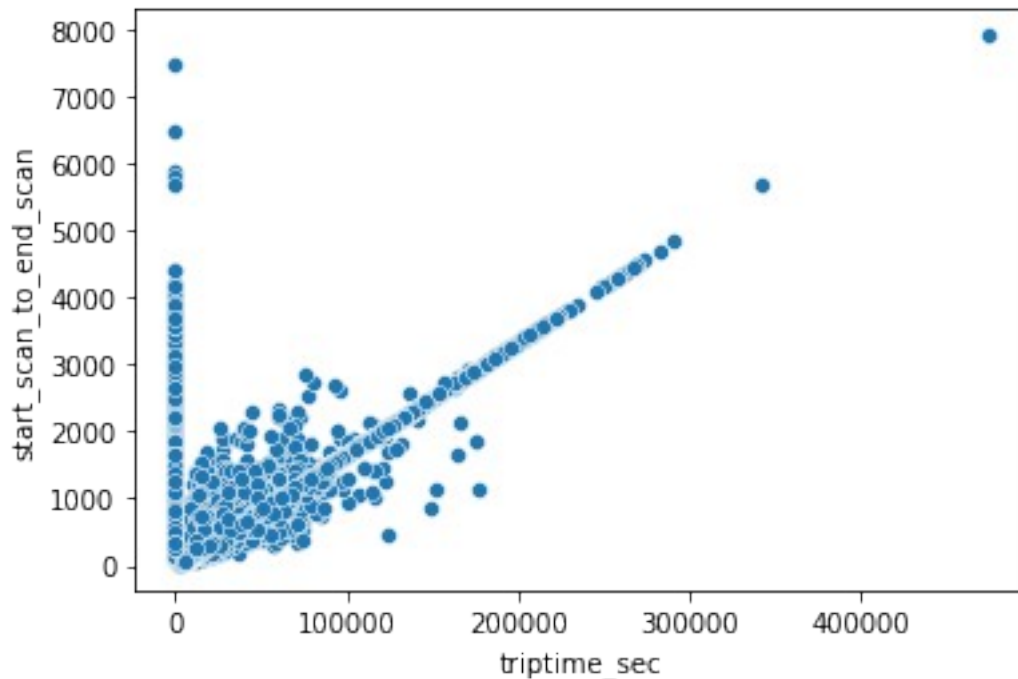
0.010496		
triptime_sec	0.745080	0.704238
0.707998		

	trip_creation_year	
trip_creation_month \		
cutoff_factor	NaN	-
0.019440		
actual_distance_to_destination	NaN	-
0.019482		
osrm_distance	NaN	-
0.018993		
start_scan_to_end_scan	NaN	-
0.019450		
segment_actual_time	NaN	-
0.017506		
segment_osrm_time	NaN	-
0.019008		
actual_time	NaN	-
0.017533		
osrm_time	NaN	-
0.020042		
segment_osrm_distance	NaN	-
0.019023		
trip_creation_year	NaN	
NaN		
trip_creation_month	NaN	
1.000000		
trip_creation_day	NaN	-
0.762671		
triptime_sec	NaN	-
0.015866		

	trip_creation_day	triptime_sec
cutoff_factor	-0.011132	0.703598
actual_distance_to_destination	-0.011104	0.703577
osrm_distance	-0.011031	0.704835
start_scan_to_end_scan	-0.014236	0.765778
segment_actual_time	-0.013692	0.745170
segment_osrm_time	-0.010119	0.701954
actual_time	-0.013676	0.745080
osrm_time	-0.010269	0.704238
segment_osrm_distance	-0.010496	0.707998
trip_creation_year	NaN	NaN
trip_creation_month	-0.762671	-0.015866
trip_creation_day	1.000000	-0.009683
triptime_sec	-0.009683	1.000000

```
#Visualization of triptime and start_scan_to_end_scan
sns.scatterplot(x=data["triptime_sec"],
y=data["start_scan_to_end_scan"])
```

```
<AxesSubplot: xlabel='triptime_sec', ylabel='start_scan_to_end_scan'>
```



Hypothesis Testiing

Pearson Test between triptime and start_scan_to_end_scan

H0: Both Variables are not correlated

Ha: Both variables are correlated

```
#Let us set siginificance level 0.05, confidence level 95%
alpha=0.05

test_statistics,p_value=pearsonr(data["triptime_sec"],
data["start_scan_to_end_scan"])
print(p_value)
if p_value < alpha:
    print("Reject Null Hypotheis, Both Variables are correlated")
else:
    print("Fail to Reject Null Hypothesis,Both Variables are not
correlated")
```

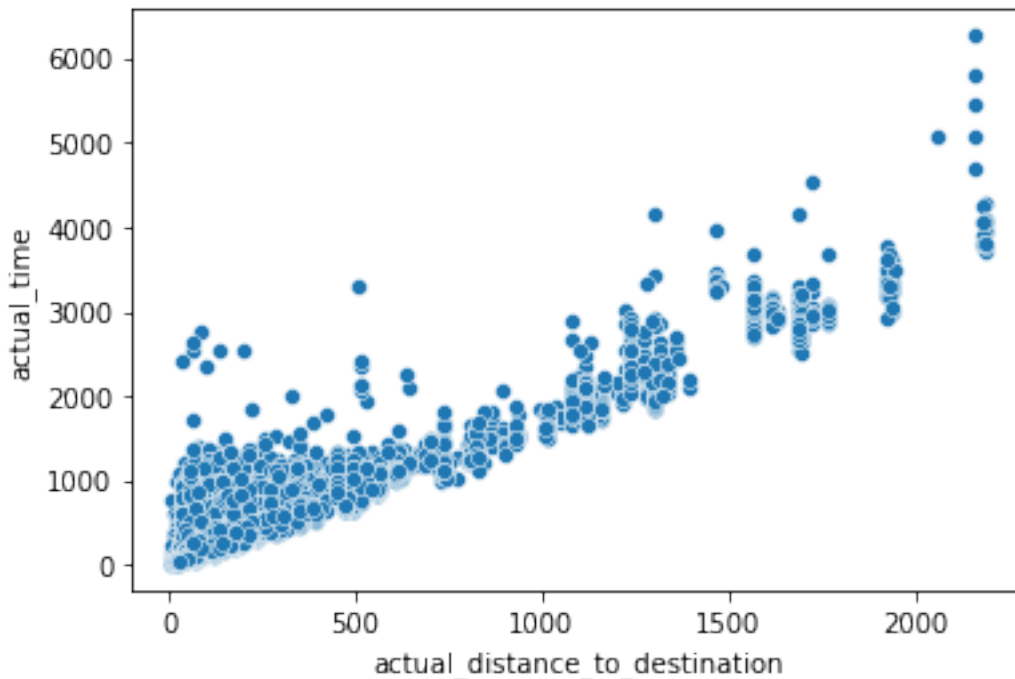
0.0

Reject Null Hypothesis, Both Variables are correlated

#Visualization between distance and time

```
sns.scatterplot(x=data["actual_distance_to_destination"],y=data["actual_time"])
```

```
<AxesSubplot: xlabel='actual_distance_to_destination',  
ylabel='actual_time'>
```



Pearson Test actual_time and actual_distance_to_destination

H0: Both Variables are not correlated

Ha: Both variables are correlated

#Let us set significance level 0.05, confidence level 95%

alpha=0.05

```
test_statistics,p_value=pearsonr(data["actual_time"],data["actual_distance_to_destination"])
```

```
print(p_value)
```

```
if p_value < alpha:
```

```
    print("Reject Null Hypothesis, Both Variables are correlated")
```

```
else:
```

```
    print("Fail to Reject Null Hypothesis,Both Variables are not correlated")
```

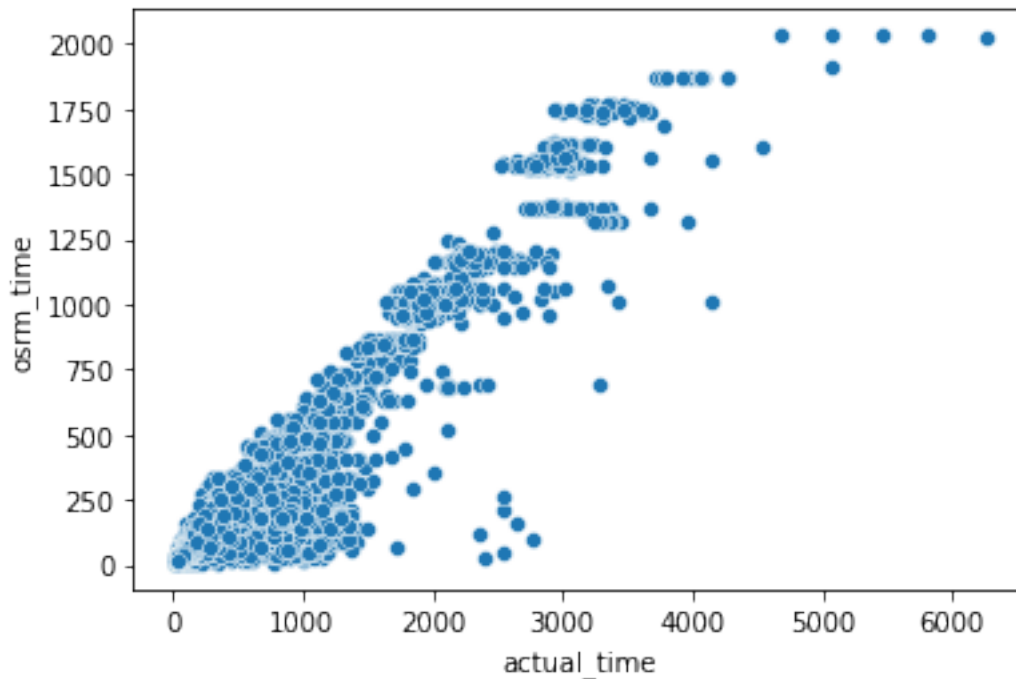

0.0

Reject Null Hypothesis, Both Variables are correlated

#Visualization between distance and time

```
sns.scatterplot(x=data["actual_time"],y=data["osrm_time"])
```

```
<AxesSubplot: xlabel='actual_time', ylabel='osrm_time'>
```



T-Test for actual_time and osrm_time

H0: Mean of actual_time and osrm_time are same ($\mu_1 = \mu_2$)

Ha: Mean of actual_time is higher than osrm_time ($\mu_1 > \mu_2$)

#Let us set significance level 0.05, confidence level 95%

alpha=0.05

```
test_statistics,p_value=ttest_ind(data["actual_time"],data["osrm_time"], alternative="greater")
```

```
print(p_value)
```

```
if p_value < alpha:
```

```
    print("Reject Null Hypothesis, Mean of actual_time and osrm_time are same")
```

```
else:
```

```
    print("Fail to Reject Null Hypothesis, Mean of actual_time is higher than osrm_time")
```

1.0113592493195362e-274

Reject Null Hypothesis, Mean of actual_time and osrm_time are same

Pearson Test actual_time and osrm_time

H0: Both Variables are not correlated

Ha: Both variables are correlated

```
#Let us set siginificance level 0.05, confidence level 95%
alpha=0.05

test_statistics,p_value=pearsonr(data["actual_time"],data["osrm_time"])
print(p_value)
if p_value < alpha:
    print("Reject Null Hypotheis, Both Variables are correlated")
else:
    print("Fail to Reject Null Hypothesis,Both Variables are not correlated")

0.0
Reject Null Hypotheis, Both Variables are correlated
```

T-Test for actual_time and segment_actual_time

H0: Mean of actual_time and segment_actual_time are same ($\mu_1 = \mu_2$)

Ha: Mean of actual_time and segment_actual_time are not same ($\mu_1 \neq \mu_2$)

```
#Let us set siginificance level 0.05, confidence level 95%
alpha=0.05

test_statistics,p_value=ttest_ind(data["actual_time"],data["segment_actual_time"])
print(p_value)
if p_value < alpha:
    print("Reject Null Hypotheis, Mean of actual_time and segment_actual_time are not same")
else:
    print("Fail to Reject Null Hypothesis,Mean of actual_time and segment_actual_time are same")

0.6419956696137739
Fail to Reject Null Hypothesis,Mean of actual_time and segment_actual_time are same
```

T-Test for osrm_time and segment_osrm_time

H0: Mean of osrm_time and segment_osrm_time are same ($\mu_1 = \mu_2$)

Ha: Mean of osrm_time and segment_osrm_time are not same ($\mu_1 \neq \mu_2$)

```
#Let us set significance level 0.05, confidence level 95%
alpha=0.05

test_statistics,p_value=ttest_ind(data["osrm_time"],data["segment_osrm_time"])
print(p_value)
if p_value < alpha:
    print("Reject Null Hypothesis, Mean of osrm_time and segment_osrm_time are not same")
else:
    print("Fail to Reject Null Hypothesis,Mean of osrm_time and segment_osrm_time are same")

1.541327181059453e-07
Reject Null Hypothesis, Mean of osrm_time and segment_osrm_time are not same
```

T-Test for osrm_distance and segment_osrm_distance

H0: Mean of osrm_distance and segment_osrm_distance are same ($\mu_1 = \mu_2$)

Ha: Mean of osrm_distance and segment_osrm_distance are not same ($\mu_1 \neq \mu_2$)

```
#Let us set significance level 0.05, confidence level 95%
alpha=0.05

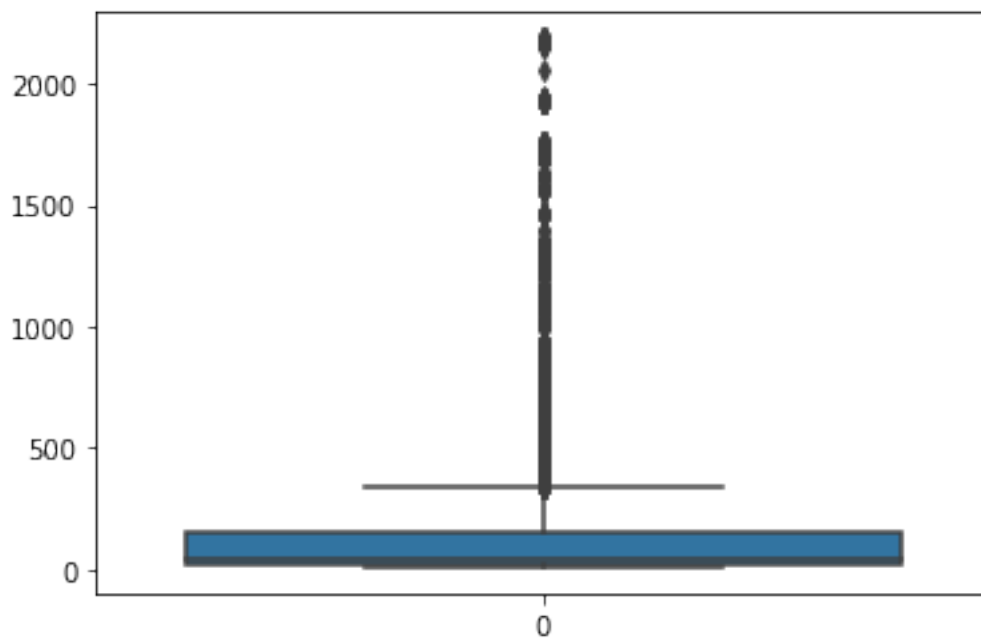
test_statistics,p_value=ttest_ind(data["osrm_distance"],data["segment_osrm_distance"])
print(p_value)
if p_value < alpha:
    print("Reject Null Hypothesis, Mean of osrm_distance and segment_osrm_distance are not same")
else:
    print("Fail to Reject Null Hypothesis,Mean of osrm_distance and segment_osrm_distance are same")

0.0001606670222265932
Reject Null Hypothesis, Mean of osrm_distance and segment_osrm_distance are not same
```

Outliers Detection Using IQR Method

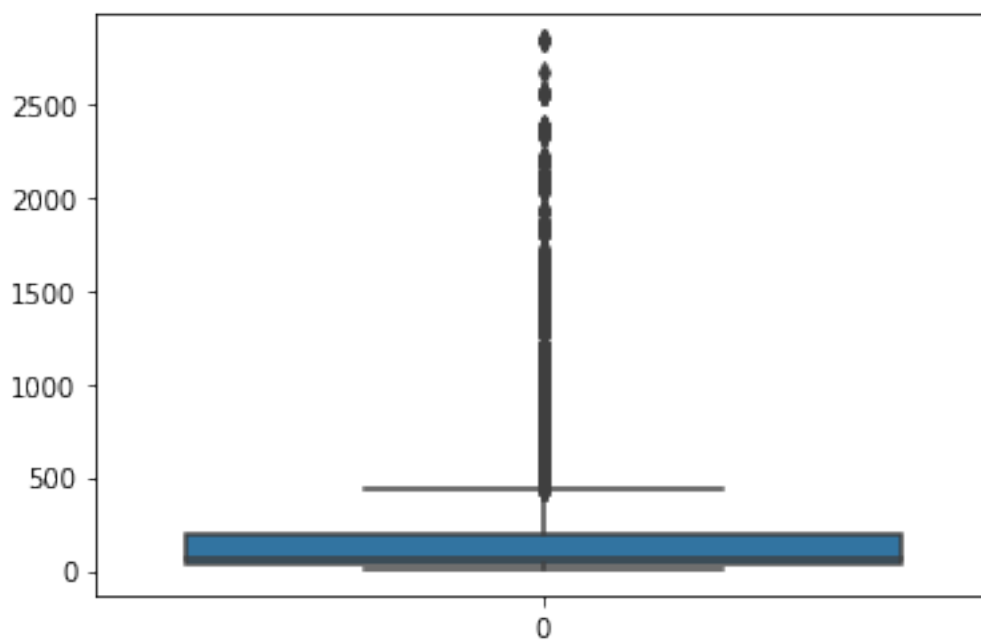
```
sns.boxplot(data["actual_distance_to_destination"])

<AxesSubplot: >
```



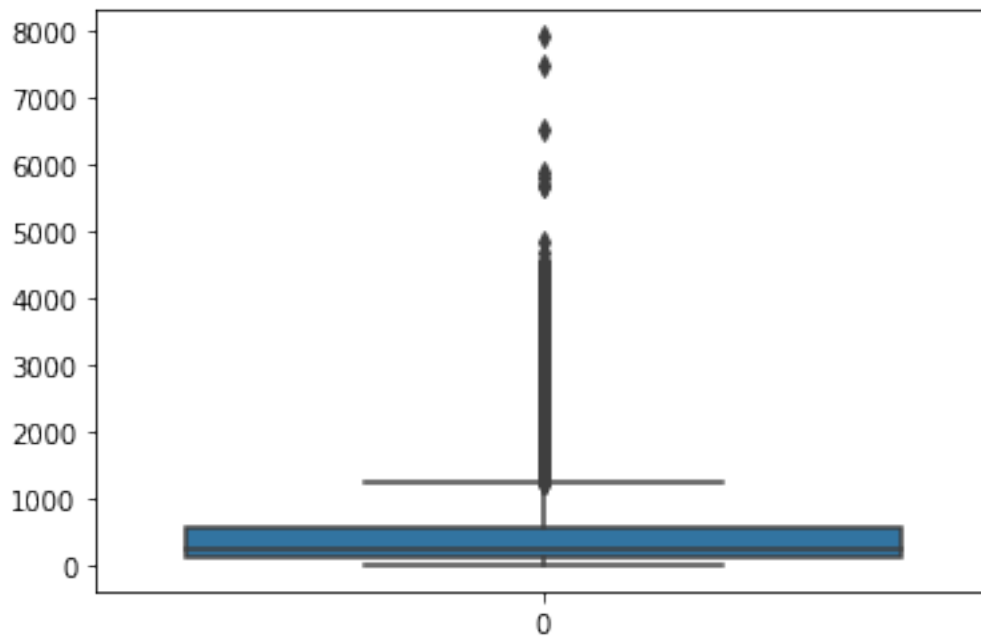
```
sns.boxplot(data["osrm_distance"])
```

<AxesSubplot: >



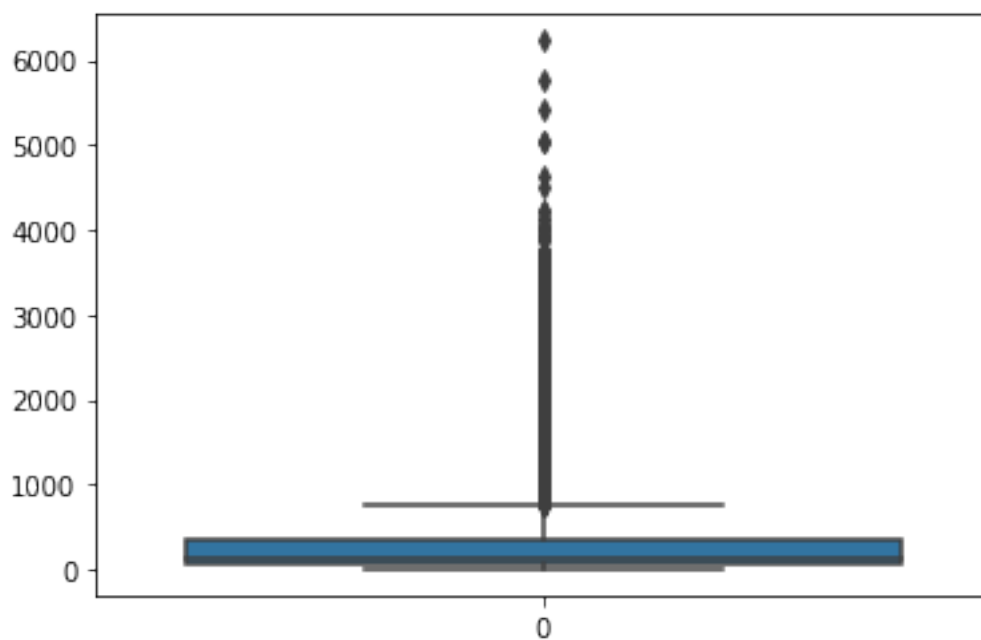
```
sns.boxplot(data["start_scan_to_end_scan"])
```

<AxesSubplot: >



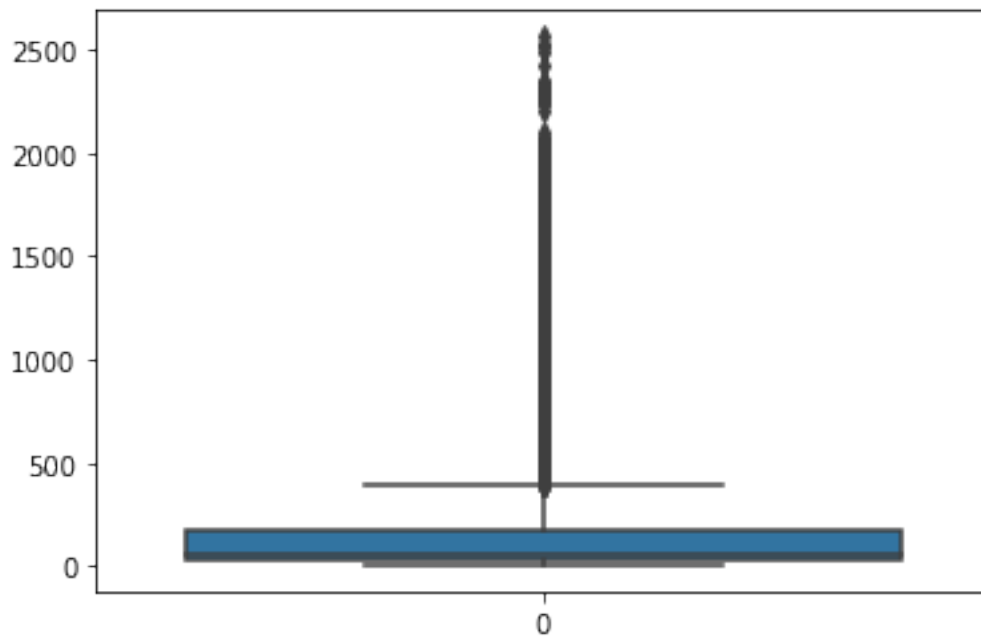
```
sns.boxplot(data["segment_actual_time"])
```

<AxesSubplot: >



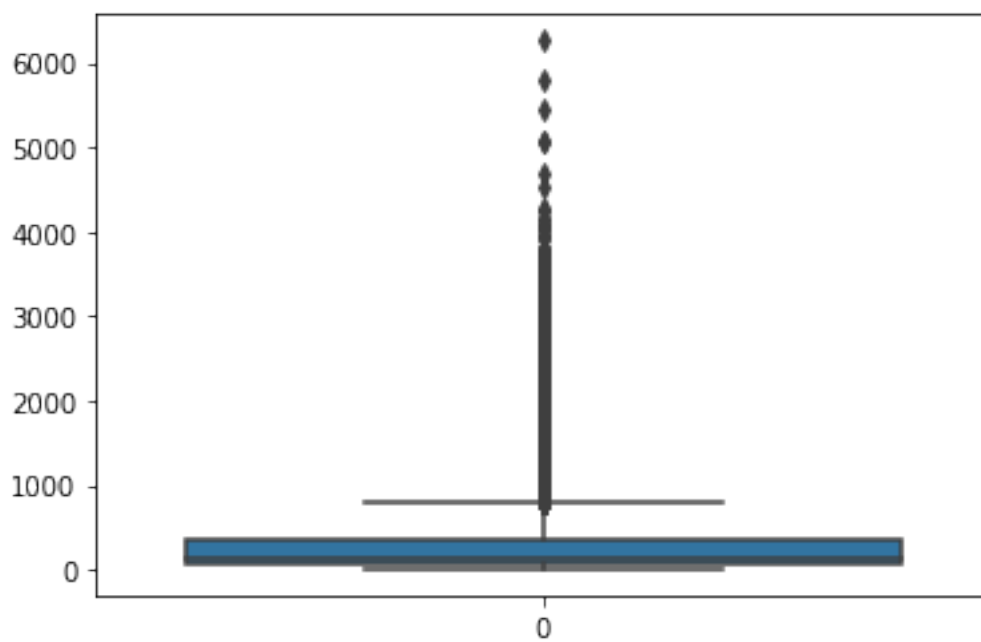
```
sns.boxplot(data["segment_osrm_time"])
```

<AxesSubplot: >



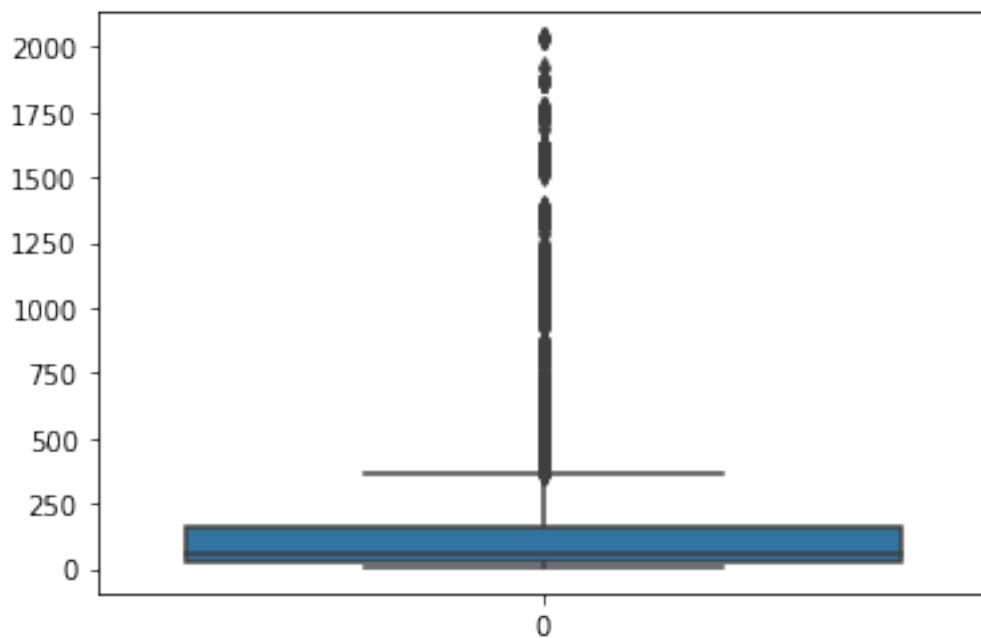
```
sns.boxplot(data["actual_time"])
```

<AxesSubplot: >



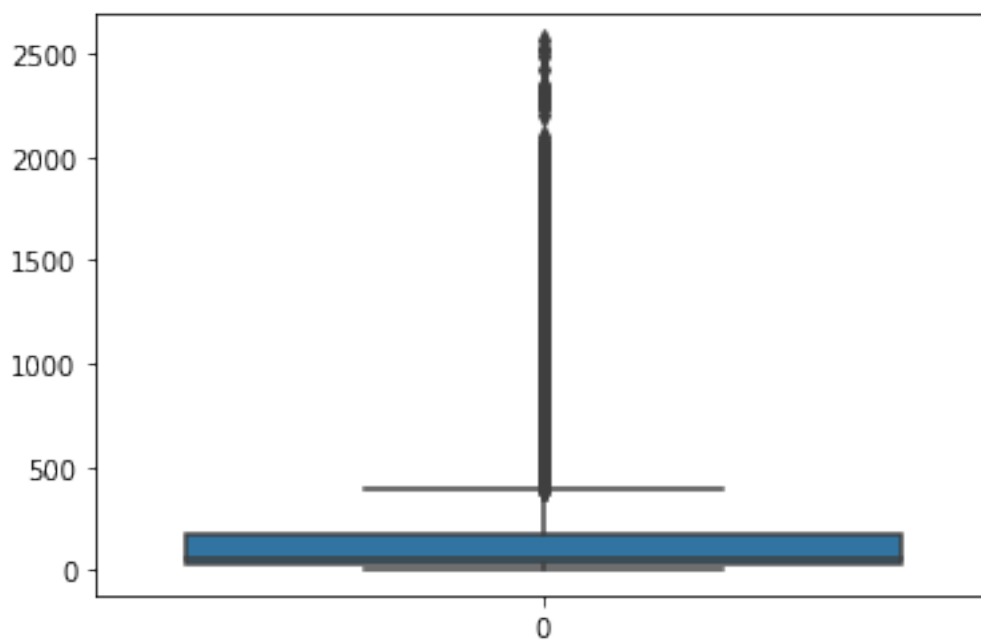
```
sns.boxplot(data["osrm_time"])
```

<AxesSubplot: >



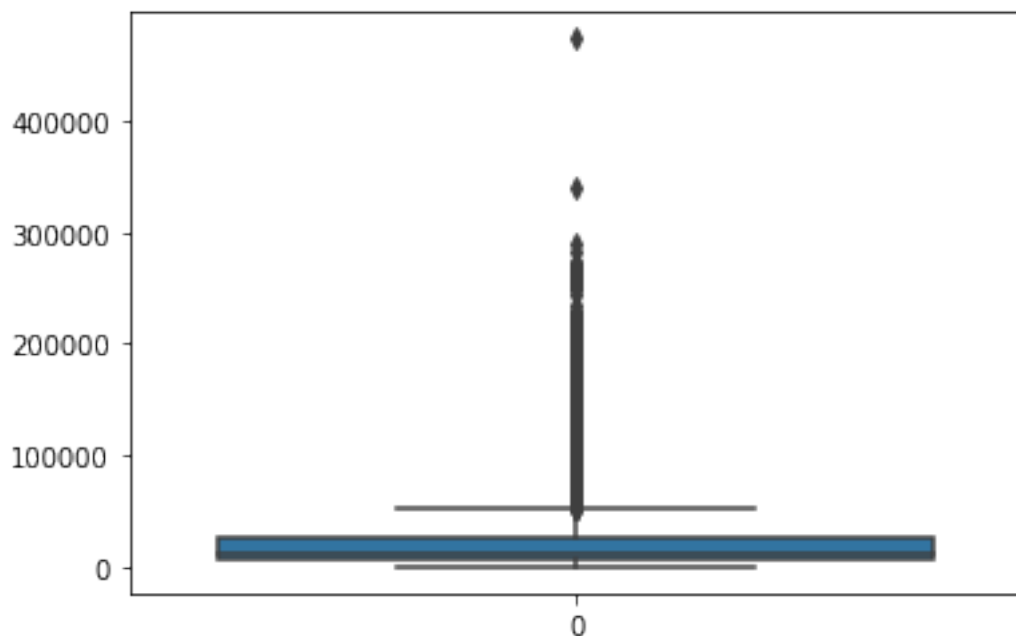
```
sns.boxplot(data["segment_osrm_time"])
```

<AxesSubplot: >



```
sns.boxplot(data["triptime_sec"])
```

<AxesSubplot: >



```
data.describe()
```

	cutoff_factor	actual_distance_to_destination	osrm_distance \
count	13892.000000	13892.000000	13892.000000
mean	159.986251	160.852618	200.437664
std	307.520122	307.627703	373.619022
min	9.000000	9.002461	9.072900
25%	21.000000	22.037144	29.802900
50%	46.000000	46.163919	61.108100
75%	148.000000	149.281573	193.689125
max	2185.000000	2187.483994	2840.081000

	start_scan_to_end_scan	segment_actual_time	segment_osrm_time
\count	13892.000000	13892.000000	13892.000000
mean	515.603657	346.118557	176.627627
std	660.357703	561.918712	316.580388
min	23.000000	9.000000	6.000000
25%	144.000000	64.000000	30.000000
50%	264.000000	136.000000	62.000000
75%	595.000000	349.000000	176.000000
max	7898.000000	6230.000000	2564.000000

	actual_time	osrm_time	segment_osrm_distance
trip_creation_year \			
count	13892.000000	13892.000000	13892.000000
13892.0			
mean	349.267492	157.980564	218.437771
2018.0			
std	567.051777	274.050917	419.933226
0.0			
min	9.000000	6.000000	9.072900
2018.0			
25%	65.000000	29.000000	31.349950
2018.0			
50%	138.000000	57.500000	65.614850
2018.0			
75%	353.000000	163.250000	204.588700
2018.0			
max	6265.000000	2032.000000	3523.632400
2018.0			

	trip_creation_month	trip_creation_day	
trip_time \			
count	13892.000000	13892.000000	
13892			
mean	9.114310	18.547653	0 days
06:45:04.119232843			
std	0.318199	7.753191	0 days
09:33:47.061593031			
min	9.000000	1.000000	0 days
00:00:00			
25%	9.000000	14.000000	0 days
01:51:56.299656750			
50%	9.000000	20.000000	0 days
03:30:54.417636			
75%	9.000000	25.000000	0 days
07:04:21.465968500			
max	10.000000	30.000000	5 days
11:38:33.117274			

	triptime_sec
count	13892.000000
mean	24304.119233
std	34427.061593
min	0.000000
25%	6716.299657
50%	12654.417636
75%	25461.465969
max	473913.117274

Outliers Treatment

#Let's remove outliers using IQR Method

sses25th = 44

sses75th = 595

iqr = sses75th - sses25th

ssesuw = sses75th + 1.5*iqr

ssesuw

1421.5

data[data["start_scan_to_end_scan"]> ssesuw]

	route_type	trip_uuid
trip_creation_time \		
875	Carting	trip-153688139008597141 2018-10-03 20:11:38.080296
1187	Carting	trip-153695358056452857 2018-09-28 21:57:19.197648
1221	Carting	trip-153695825653985603 2018-09-30 07:30:32.488364
1316	Carting	trip-153696880159964742 2018-09-21 20:55:53.211057
1402	Carting	trip-153697923702522443 2018-09-23 15:30:38.146740
...
14744	FTL	trip-153860352246282031 2018-09-24 05:06:56.558662
14748	FTL	trip-153860451596867762 2018-09-24 05:06:56.558662
14754	FTL	trip-153860570045461434 2018-09-24 05:06:56.558662
14764	FTL	trip-153860698042160875 2018-09-24 05:06:56.558662
14773	FTL	trip-153860879439383883 2018-09-24 05:06:56.558662

	source_center	source_name \
875	IND395023AAD	Surat_Central_I_4 (Gujarat)
1187	IND431112AAB	Sillod_ZebaTWR_D (Maharashtra)
1221	IND530012AAA	Visakhapatnam_Gajuwaka_IP (Andhra Pradesh)
1316	IND395023AAD	Surat_Central_I_4 (Gujarat)
1402	IND211002AAB	Allahabad_Central_H_1 (Uttar Pradesh)
...
14744	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)
14748	IND712311AAA	Kolkata_Dankuni_HB (West Bengal)
14754	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)
14764	IND131028AAB	Sonipat_Kundli_H (Haryana)
14773	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)

	destination_center	destination_name \
875	IND396321AAA	Bilimora_DC (Gujarat)
1187	IND431203AAA	Jalna_BhgynaGr_D (Maharashtra)
1221	IND530012AAA	Visakhapatnam_Gajuwaka_IP (Andhra Pradesh)
1316	IND396321AAA	Bilimora_DC (Gujarat)
1402	IND212402AAA	Phulpur_Shekhpur_D (Uttar Pradesh)
...
14744	IND712311AAA	Kolkata_Dankuni_HB (West Bengal)
14748	IND712311AAA	Kolkata_Dankuni_HB (West Bengal)
14754	IND834002AAB	Ranchi_Hub (Jharkhand)
14764	IND131028AAB	Sonipat_Kundli_H (Haryana)
14773	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)

	od_start_time	od_end_time
cutoff_factor \		
875	2018-09-13 23:29:50.086266	2018-09-14 02:58:24.884963
137		
1187	2018-09-15 04:40:33.384907	2018-09-16 01:06:53.762074
207		
1221	2018-09-14 20:50:56.540060	2018-09-15 23:00:45.715950
194		
1316	2018-09-14 23:46:41.600072	2018-09-15 03:21:56.351119
113		
1402	2018-09-15 02:40:37.025475	2018-09-15 07:54:57.848178
93		
...
...		
14744	2018-10-03 21:52:02.463089	2018-10-05 09:06:25.403171
1300		
14748	2018-10-03 22:08:35.968978	2018-10-04 22:26:30.408004
159		
14754	2018-10-03 22:28:20.454881	2018-10-05 08:39:47.996375
1010		
14764	2018-10-05 08:35:15.664489	2018-10-05 08:35:15.664489
1321		
14773	2018-10-06 04:27:23.392375	2018-10-06 04:27:23.392375
1931		

...	actual_time	osrm_time	segment_osrm_distance	
source_state \				
875 ...	1108.0	145.0	271.4230	
Gujarat				
1187 ...	586.0	169.0	295.9635	
Maharashtra				
1221 ...	303.0	169.0	228.7358	Andhra Pradesh
1316 ...	258.0	127.0	206.7191	
Gujarat				
1402 ...	1204.0	90.0	117.4880	Uttar Pradesh
...	
...				
14744 ...	1930.0	1016.0	1497.6331	
Haryana				
14748 ...	1342.0	145.0	197.2656	West Bengal
14754 ...	1625.0	851.0	1222.2127	
Haryana				
14764 ...	2003.0	1166.0	1747.4544	
Haryana				
14773 ...	3307.0	1739.0	2600.9869	
Haryana				
	destination_state	trip_creation_year	trip_creation_month	\
875	Gujarat	2018.0	10.0	
1187	Maharashtra	2018.0	9.0	
1221	Andhra Pradesh	2018.0	9.0	
1316	Gujarat	2018.0	9.0	
1402	Uttar Pradesh	2018.0	9.0	
...	
14744	West Bengal	2018.0	9.0	
14748	West Bengal	2018.0	9.0	
14754	Jharkhand	2018.0	9.0	
14764	Haryana	2018.0	9.0	
14773	Haryana	2018.0	9.0	
	trip_creation_day	trip_time	triptime_sec	
875	3.0 0 days	03:28:34.798697	12514.798697	
1187	28.0 0 days	20:26:20.377167	73580.377167	
1221	30.0 1 days	02:09:49.175890	94189.175890	
1316	21.0 0 days	03:35:14.751047	12914.751047	
1402	23.0 0 days	05:14:20.822703	18860.822703	
...	
14744	24.0 1 days	11:14:22.940082	126862.940082	
14748	24.0 1 days	00:17:54.439026	87474.439026	
14754	24.0 1 days	10:11:27.541494	123087.541494	
14764	24.0 0 days	00:00:00	0.000000	

```
14773          24.0          0 days 00:00:00          0.000000
```

```
[1040 rows x 25 columns]
```

```
#We will drop outliers which we have found using IQR Method  
data.drop(data[data["start_scan_to_end_scan"]> ssesuw].index,  
inplace=True)
```

```
data.describe()
```

	cutoff_factor	actual_distance_to_destination	osrm_distance \
count	12852.000000	12852.000000	12852.000000
mean	88.108077	88.962952	113.436786
std	108.676646	108.964263	135.904653
min	9.000000	9.002461	9.072900
25%	21.000000	21.513693	28.613375
50%	39.000000	39.995569	51.578350
75%	117.000000	118.535713	151.928175
max	830.000000	830.517272	970.943400

	start_scan_to_end_scan	segment_actual_time	segment_osrm_time
count	12852.000000	12852.000000	12852.000000
mean	363.109088	216.271709	103.763305
std	320.783878	237.050219	117.762542
min	23.000000	9.000000	6.000000
25%	137.000000	61.000000	28.000000
50%	240.000000	119.000000	56.000000
75%	471.000000	282.000000	144.000000
max	1421.000000	1372.000000	867.000000

	actual_time	osrm_time	segment_osrm_distance
trip_creation_year \			
count	12852.000000	12852.000000	12852.000000
12852.0			
mean	218.170557	94.566838	121.064327
2018.0			
std	238.554090	105.277546	146.155991
0.0			
min	9.000000	6.000000	9.072900
2018.0			
25%	62.000000	27.750000	29.653100
2018.0			

```

50%      120.000000      52.000000      56.815650
2018.0
75%      284.000000      125.000000      159.915625
2018.0
max      1372.000000      712.000000      1150.617300
2018.0

      trip_creation_month  trip_creation_day
trip_time \
count      12852.000000      12852.000000
12852
mean          9.114846          18.584967  0 days
05:00:24.581706652
std          0.318848          7.786337  0 days
04:58:46.808724515
min          9.000000          1.000000      0 days
00:00:00
25%          9.000000          14.000000  0 days
01:51:31.947565250
50%          9.000000          20.000000      0 days
03:21:36.093887
75%          9.000000          25.000000  0 days
06:17:26.963298250
max          10.000000          30.000000      2 days
01:09:57.136511

      triptime_sec
count      12852.000000
mean      18024.581707
std      17926.808725
min          0.000000
25%      6691.947565
50%      12096.093887
75%      22646.963298
max      176997.136511

```

Here We can observe that by removing outliers in start_scan_to_end_scan column, other columns max values has been decreased significantly and further dropping columns will lead to loss of valuable data

Data Encoding

```

data_encoding=data.copy()

data_encoding.shape

(12852, 25)

```

Label Encoding

```
#Here We will use label encoder for encoding route_type column
le = LabelEncoder()

col="route_type"
data_encoding[col].value_counts()

Carting      8503
FTL          4349
Name: route_type, dtype: int64

data_encoding[col]=le.fit_transform(data_encoding[col])
data_encoding[col].value_counts()

0      8503
1      4349
Name: route_type, dtype: int64
```

Target Encoding

```
from category_encoders import TargetEncoder

te=TargetEncoder()

#Here we will do target encoding for
"source_center","source_name","destination_center","destination_name",
"source_state","destination_state" columns
columns=["source_center","source_name","destination_center","destinati
on_name","source_state","destination_state"]
for col in columns:
    data_encoding[col]=te.fit_transform(data_encoding[col],
data_encoding["route_type"])

data_encoding.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 12852 entries, 0 to 14786
Data columns (total 25 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   route_type                            12852 non-null  int32
1   trip_uuid                             12852 non-null  object
2   trip_creation_time                    12852 non-null  datetime64[ns]
3   source_center                         12852 non-null  float64
4   source_name                           12852 non-null  float64
5   destination_center                    12852 non-null  float64
6   destination_name                      12852 non-null  float64
7   od_start_time                        12852 non-null  datetime64[ns]
```

```

8   od_end_time          12852 non-null datetime64[ns]
9   cutoff_factor        12852 non-null int64
10  actual_distance_to_destination 12852 non-null float64
11  osrm_distance         12852 non-null float64
12  start_scan_to_end_scan 12852 non-null float64
13  segment_actual_time   12852 non-null float64
14  segment_osrm_time     12852 non-null float64
15  actual_time           12852 non-null float64
16  osrm_time             12852 non-null float64
17  segment_osrm_distance 12852 non-null float64
18  source_state          12852 non-null float64
19  destination_state     12852 non-null float64
20  trip_creation_year    12852 non-null float64
21  trip_creation_month   12852 non-null float64
22  trip_creation_day     12852 non-null float64
23  trip_time             12852 non-null timedelta64[ns]
24  triptime_sec          12852 non-null float64
dtypes: datetime64[ns](3), float64(18), int32(1), int64(1), object(1),
timedelta64[ns](1)
memory usage: 2.5+ MB

```

```

data_encoding.drop(["trip_uuid", "trip_creation_time", "od_start_time",
"od_end_time", "trip_time"], axis=1, inplace=True)

```

```
data_encoding
```

	route_type	source_center	source_name	destination_center \
0	0	0.233481	0.233481	2.405789e-01
1	0	0.026667	0.026667	5.140380e-08
2	0	0.265919	0.265919	2.943634e-01
3	0	0.019398	0.019398	2.261087e-01
4	0	0.000924	0.000924	4.186833e-06
...
14778	1	0.432241	0.432241	8.583065e-01
14780	1	0.636225	0.636225	9.449722e-01
14783	1	0.888157	0.888157	8.955545e-01
14785	1	0.636225	0.636225	6.362248e-01
14786	1	0.424472	0.424472	5.036211e-01

	destination_name	cutoff_factor	actual_distance_to_destination
\			
0	2.405789e-01	72	73.186911
1	5.140380e-08	17	17.175274
2	2.943634e-01	24	24.597048
3	2.261087e-01	9	9.100510
4	4.186833e-06	22	22.424210

...
14778	8.583065e-01	143	144.794266
14780	9.449722e-01	174	176.546661
14783	8.955545e-01	192	194.552260
14785	6.362248e-01	84	84.743813
14786	5.036211e-01	65	66.081533

	osrm_distance	start_scan_to_end_scan	segment_actual_time \
0	85.1110	180.0	141.0
1	19.6800	100.0	59.0
2	28.0647	189.0	60.0
3	12.0184	98.0	24.0
4	28.9203	146.0	64.0
...
14778	191.0458	852.0	270.0
14780	220.3007	678.0	378.0
14783	229.2052	1017.0	845.0
14785	102.3828	256.0	186.0
14786	80.5787	353.0	274.0

	segment_osrm_time	actual_time	osrm_time
segment_osrm_distance \			
0	65.0	143.0	68.0
84.1894			
1	16.0	59.0	15.0
19.8766			
2	23.0	61.0	23.0
28.0647			
3	13.0	24.0	13.0
12.0184			
4	34.0	64.0	34.0
28.9203			
...
.			
14778	136.0	272.0	139.0
172.9107			
14780	194.0	378.0	192.0
212.8530			
14783	178.0	847.0	178.0
232.5811			
14785	92.0	187.0	92.0
107.6915			
14786	67.0	275.0	68.0
80.5787			

	source_state	destination_state	trip_creation_year	\
0	0.132353	0.167293	2018.0	
1	0.213544	0.189456	2018.0	
2	0.263959	0.277888	2018.0	
3	0.263959	0.277888	2018.0	
4	0.132353	0.167293	2018.0	
...
14778	0.417819	0.398413	2018.0	
14780	0.456364	0.505843	2018.0	
14783	0.940594	0.940594	2018.0	
14785	0.456364	0.505843	2018.0	
14786	0.132353	0.167293	2018.0	

	trip_creation_month	trip_creation_day	triptime_sec	
0	9.0	20.0	0.000000	
1	9.0	20.0	6029.696112	
2	9.0	20.0	0.000000	
3	9.0	20.0	5880.338041	
4	9.0	20.0	10586.899446	
...
14778	9.0	24.0	51184.266566	
14780	9.0	24.0	40779.500123	
14783	9.0	24.0	61169.217828	
14785	9.0	24.0	0.000000	
14786	9.0	24.0	0.000000	

[12852 rows x 20 columns]

Standardization

#Here We will use MinMaxScaler method for standardizing dataframe

```
scaler=MinMaxScaler()
```

```
std_data=scaler.fit_transform(data_encoding)
```

```
std_data=pd.DataFrame(std_data, columns=data_encoding.columns)
```

std_data

	route_type	source_center	source_name	destination_center	\
0	0.0	0.234251	0.234251	2.521111e-01	
1	0.0	0.026755	0.026755	5.386383e-08	
2	0.0	0.266796	0.266796	3.084738e-01	
3	0.0	0.019462	0.019462	2.369473e-01	
4	0.0	0.000928	0.000928	4.387526e-06	
...
12847	1.0	0.433666	0.433666	8.994497e-01	
12848	1.0	0.638322	0.638322	9.902697e-01	
12849	1.0	0.891085	0.891085	9.384832e-01	

12850	1.0	0.638322	0.638322	6.667225e-01
12851	1.0	0.425871	0.425871	5.277623e-01

	destination_name	cutoff_factor	actual_distance_to_destination
\			
0	2.521111e-01	0.076736	0.078129
1	5.386383e-08	0.009744	0.009948
2	3.084738e-01	0.018270	0.018983
3	2.369473e-01	0.000000	0.000119
4	4.387526e-06	0.015834	0.016338
...
12847	8.994497e-01	0.163216	0.165294
12848	9.902697e-01	0.200974	0.203945
12849	9.384832e-01	0.222899	0.225863
12850	6.667225e-01	0.091352	0.092197
12851	5.277623e-01	0.068210	0.069480

	osrm_distance	start_scan_to_end_scan	segment_actual_time	\
0	0.079052	0.112303	0.096845	
1	0.011028	0.055079	0.036684	
2	0.019745	0.118741	0.037417	
3	0.003062	0.053648	0.011005	
4	0.020634	0.087983	0.040352	
...	
12847	0.189186	0.592990	0.191489	
12848	0.219601	0.468526	0.270726	
12849	0.228859	0.711016	0.613353	
12850	0.097009	0.166667	0.129861	
12851	0.074340	0.236052	0.194424	

	segment_osrm_time	actual_time	osrm_time
segment_osrm_distance			
0	0.068525	0.098313	0.087819
0.065803			
1	0.011614	0.036684	0.012748
0.009464			
2	0.019744	0.038151	0.024079
0.016637			
3	0.008130	0.011005	0.009915
0.002580			

```

4          0.032520    0.040352    0.039660
0.017386
...          ...          ...          ...
.
12847      0.150987    0.192957    0.188385
0.143523
12848      0.218351    0.270726    0.263456
0.178513
12849      0.199768    0.614820    0.243626
0.195795
12850      0.099884    0.130594    0.121813
0.086391
12851      0.070848    0.195158    0.087819
0.062640

      source_state destination_state trip_creation_year \
0          0.108790          0.094519          0.0
1          0.197365          0.118627          0.0
2          0.252366          0.214823          0.0
3          0.252366          0.214823          0.0
4          0.108790          0.094519          0.0
...          ...          ...          ...
12847      0.420218          0.345928          0.0
12848      0.462268          0.462789          0.0
12849      0.990537          0.935705          0.0
12850      0.462268          0.462789          0.0
12851      0.108790          0.094519          0.0

      trip_creation_month trip_creation_day triptime_sec
0          0.0          0.655172    0.000000
1          0.0          0.655172    0.034067
2          0.0          0.655172    0.000000
3          0.0          0.655172    0.033223
4          0.0          0.655172    0.059814
...          ...          ...          ...
12847      0.0          0.793103    0.289181
12848      0.0          0.793103    0.230396
12849      0.0          0.793103    0.345594
12850      0.0          0.793103    0.000000
12851      0.0          0.793103    0.000000

[12852 rows x 20 columns]

```

Business Insights

By doing Hypothesis testing between osrm data and actual data, we can observe that mean of both data is not the same.

Distance and time attributes are highly correlated, so its obvious that distance between places will matter in speedy delivery

Maximum orders are found from Maharashtra, so we can say more customers in the state.

Minimum trips are from North-Eastern states so business needs improvement in that states

The busiest warehouses are Gurgaon_Bilaspur, Bhiwandi, and Bangalore, So, They should be more focused.

The Busiest route is Bangalore_Nalamngla_H (Karnataka) to Bengaluru_KGAirport_HB (Karnataka). The average distance between them is 28.03 and the average time taken for the given trip is 87.87

Recommendations

From the above analysis, It can be observed that the actual time taken for delivery is higher compared to osrm time. So we can optimize our services using osrm.

We have the busiest route in Bangaluru, so we can increase our service by providing different outlets and increasing the manpower

In Maharashtra, we have the highest number of trips, so we should increase outlets in the state.

In North-Eastern states, we have very less business, so we need to optimize their condition and also provide marketing to increase services.

We have the busiest warehouse in Gurgaon_Bilaspur, so we need to increase the number of warehouses or increase manpower to efficiently handle the load.

OSRM provides us best minimal distance