

DELHIVERY - Business CaseStudy

Introduction:

- **Delhivery**, established in 2011, is India's foremost logistics and supply chain service provider, offering a comprehensive range of solutions including express parcel transportation, warehousing, and last-mile delivery.
- Leveraging advanced technology and a vast delivery network, Delhivery efficiently manages nationwide movement of goods, earning trust across businesses of all sizes for its dedication to innovation and customer satisfaction.
- As the largest fully integrated player in India by revenue in Fiscal 2021, Delhivery aims to lead the industry by pioneering the commerce operating system, driven by top-tier infrastructure, logistics operations, and innovative data intelligence initiatives led by its Data team.

Why this case study?

Delhivery aims to establish itself as the premier player in the logistics industry. This case study is of paramount importance as it aligns with the company's core objectives and operational excellence.

It provides a practical framework for understanding and processing data, which is integral to their operations. By leveraging data engineering pipelines and data analysis techniques, Delhivery can achieve several critical goals.

First, it allows them to ensure data integrity and quality by addressing missing values and structuring the dataset appropriately.

Second, it enables the extraction of valuable features from raw data, which can be utilized for building accurate forecasting models.

Moreover, it facilitates the identification of patterns, insights, and actionable recommendations crucial for optimizing their logistics operations.

By conducting hypothesis testing and outlier detection, Delhivery can refine their processes and further enhance the quality of service they provide.

How can you help here?

The company wants to understand and process the data coming out of data engineering pipelines:

- Clean, sanitize and manipulate data to get useful features out of raw fields
- Make sense out of the raw data and help the data science team to build forecasting models on it.

Features of the dataset:

- Column Profiling:

Feature	Description
data	tells whether the data is testing or training data
trip_creation_time	Timestamp of trip creation
route_schedule_uuid	Unique ID for a particular route schedule
route_type	Transportation type
a. FTL—Full Truck Load	FTL shipments get to the destination sooner, as the truck is making no other pickups or drop-offs along the way
b. Carting	Handling system consisting of small vehicles (carts)
trip_uuid	Unique ID given to a particular trip (A trip may include different source and destination centers)
source_center	Source ID of trip origin
source_name	Source Name of trip origin
destination_center	Destination ID
destination_name	Destination Name
od_start_time	Trip start time
od_end_time	Trip end time
start_scan_to_end_scan	Time taken to deliver from source to destination
is_cutoff	Unknown field
cutoff_factor	Unknown field
cutoff_timestamp	Unknown field
actual_distance_to_destination	Distance in kms between source and destination warehouse
actual_time	Actual time taken to complete the delivery (Cumulative)
osrm_time	An open-source routing engine time calculator which computes the shortest path between points in a given map (Includes usual traffic, distance through major and minor roads) and gives the time (Cumulative)
osrm_distance	An open-source routing engine which computes the shortest path between points in a given map (Includes usual traffic, distance through major and minor roads) (Cumulative)
factor	Unknown field
segment_actual_time	This is a segment time. Time taken by the subset of the package delivery
segment_osrm_time	This is the OSRM segment time. Time taken by the

Feature	Description
segment_osrm_distance	subset of the package delivery
segment_factor	This is the OSRM distance. Distance covered by subset of the package delivery
segment_factor	Unknown field

```

# importing the required modules and packages

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import re
from scipy.stats import norm,zscore,boxcox,probplot
from scipy.stats import ttest_ind,ttest_rel,mannwhitneyu,wilcoxon
from scipy.stats import shapiro,levene,kstest,anderson
import statsmodels.api as sm
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler , MinMaxScaler ,
OneHotEncoder
import warnings
warnings.filterwarnings('ignore')

# pd_reading the data
delhivery_data = pd.read_csv('delhivery_data.csv')

# setting the option of displaying all the columns
pd.set_option('display.max_columns', 50)

# making a deep copy for backup
dd = delhivery_data.copy()
dd.head()

      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

                           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

      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)

      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)

      od_start_time          od_end_time  \
0  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
1  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
2  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
3  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797
4  2018-09-20 03:21:32.418600  2018-09-20 04:47:45.236797

      start_scan_to_end_scan  is_cutoff  cutoff_factor  \
0                  86.0      True            9
1                  86.0      True           18
2                  86.0      True           27
3                  86.0      True           36
4                  86.0     False           39

      cutoff_timestamp  actual_distance_to_destination
actual_time  \
0             2018-09-20 04:27:55                      10.435660
14.0
1             2018-09-20 04:17:55                      18.936842
24.0
2             2018-09-20 04:01:19.505586                  27.637279
40.0
3             2018-09-20 03:39:57                      36.118028
62.0
4             2018-09-20 03:33:55                      39.386040
68.0

      osrm_time  osrm_distance    factor  segment_actual_time
segment_osrm_time  \
0            11.0         11.9653  1.272727                  14.0
11.0
1            20.0         21.7243  1.200000                  10.0

```

```

9.0
2      28.0      32.5395  1.428571      16.0
7.0
3      40.0      45.5620  1.550000      21.0
12.0
4      44.0      54.2181  1.545455      6.0
5.0

    segment_osrm_distance  segment_factor
0              11.9653      1.272727
1              9.7590      1.111111
2             10.8152      2.285714
3             13.0224      1.750000
4              3.9153      1.200000

```

Exploration of data :

```

dd.shape
(144867, 24)

dd.columns
Index(['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'],
      dtype='object')

dd.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 24 columns):
 #   Column           Non-Null Count Dtype
 --- 
 0   data             144867 non-null object
 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

```

Statistical Summary

```
dd.describe().T
```

		count	mean	std
min \				
start_scan_to_end_scan	20.000000	144867.0	961.262986	1037.012769
cutoff_factor	9.000000	144867.0	232.926567	344.755577
actual_distance_to_destination	9.000045	144867.0	234.073372	344.990009
actual_time	9.000000	144867.0	416.927527	598.103621
osrm_time	6.000000	144867.0	213.868272	308.011085
osrm_distance	9.008200	144867.0	284.771297	421.119294
factor	0.144000	144867.0	2.120107	1.715421
segment_actual_time	244.000000	144867.0	36.196111	53.571158 -
segment_osrm_time	0.000000	144867.0	18.507548	14.775960
segment_osrm_distance	0.000000	144867.0	22.829020	17.860660
segment_factor	23.444444	144867.0	2.218368	4.847530 -

```

                25%      50%      75%  \
start_scan_to_end_scan    161.000000  449.000000  1634.000000
cutoff_factor             22.000000   66.000000  286.000000
actual_distance_to_destination  23.355874  66.126571  286.708875
actual_time               51.000000  132.000000  513.000000
osrm_time                 27.000000   64.000000  257.000000
osrm_distance              29.914700  78.525800  343.193250
factor                     1.604264   1.857143   2.213483
segment_actual_time        20.000000   29.000000   40.000000
segment_osrm_time          11.000000   17.000000   22.000000
segment_osrm_distance      12.070100  23.513000  27.813250
segment_factor              1.347826   1.684211   2.250000

                                         max
start_scan_to_end_scan    7898.000000
cutoff_factor             1927.000000
actual_distance_to_destination  1927.447705
actual_time               4532.000000
osrm_time                 1686.000000
osrm_distance              2326.199100
factor                     77.387097
segment_actual_time        3051.000000
segment_osrm_time          1611.000000
segment_osrm_distance      2191.403700
segment_factor              574.250000

dd.describe(include=object).T

                count unique  \
data           144867      2
trip_creation_time  144867  14817
route_schedule_uuid  144867  1504
route_type         144867      2
trip_uuid          144867  14817
source_center       144867  1508
source_name         144574  1498
destination_center  144867  1481
destination_name    144606  1468
od_start_time       144867  26369
od_end_time         144867  26369
cutoff_timestamp    144867  93180

                                         top
freq
data
104858
trip_creation_time          2018-09-28 05:23:15.359220
101
route_schedule_uuid thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...

```

```

1812
route_type FTL
99660
trip_uuid trip-153811219535896559
101
source_center IND000000ACB
23347
source_name Gurgaon_Bilaspur_HB (Haryana)
23347
destination_center IND000000ACB
15192
destination_name Gurgaon_Bilaspur_HB (Haryana)
15192
od_start_time 2018-09-21 18:37:09.322207
81
od_end_time 2018-09-24 09:59:15.691618
81
cutoff_timestamp 2018-09-24 05:19:20
40

```

####Duplicate Detection

```

dd[dd.duplicated()]

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: []

```

Insights

- The dataset does not contain any duplicates.

Null Detection

```

dd.isna().any()

data False
trip_creation_time False
route_schedule_uuid False
route_type False
trip_uuid False
source_center False
source_name True

```

```

destination_center           False
destination_name             True
od_start_time                False
od_end_time                  False
start_scan_to_end_scan      False
is_cutoff                     False
cutoff_factor                 False
cutoff_timestamp              False
actual_distance_to_destination False
actual_time                   False
osrm_time                     False
osrm_distance                 False
factor                        False
segment_actual_time          False
segment_osrm_time             False
segment_osrm_distance         False
segment_factor                 False
dtype: bool

dd.isnull().sum()

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

def missing_data(df):
    total_missing_df = df.isnull().sum().sort_values(ascending =False)
    percent_missing_df =

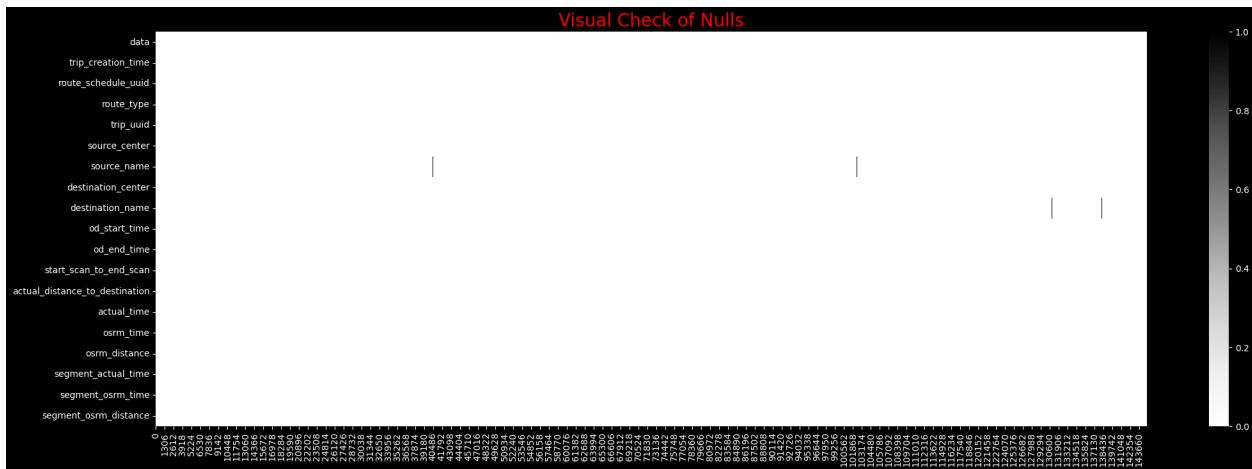
```

```
(df.isnull().sum()/df.isna().count()*100).sort_values(ascending=False)
# ----> /len(dd)
    missing_data_df = pd.concat([total_missing_df,
percent_missing_df], axis=1, keys=['Total', 'Percent'])
    return missing_data_df

missing_pct = missing_data(dd)
missing_pct[missing_pct['Total']>0]

      Total  Percent
source_name        293  0.202254
destination_name   261  0.180165

plt.figure(figsize=(25,8))
plt.style.use('dark_background')
sns.heatmap(dd.isnull().T,cmap='Greys')
plt.title('Visual Check of Nulls',fontsize=20,color='r')
plt.show()
```



```
# Dropping unknown fields

unknown_fields = ['is_cutoff', 'cutoff_factor', 'cutoff_timestamp',
'factor', 'segment_factor']
dd = dd.drop(columns = unknown_fields)

dd.sample()

      data          trip_creation_time \
133488  test  2018-09-30 05:56:48.299467

                                         route_schedule_uuid
route_type \
133488 thanos::sroute:6be6529b-f2ad-4714-b7ab-ac58f24...       FTL

      trip_uuid source_center
```

```

source_name \
133488 trip-153828700829921150 IND000000ACB Gurgaon_Bilaspur_HB
(Haryana)

            destination_center           destination_name \
133488          IND600056AAB  MAA_Poonamallee_HB (Tamil Nadu)

                  od_start_time           od_end_time \
133488  2018-09-30 05:56:48.299467  2018-10-02 10:36:25.970169

      start_scan_to_end_scan  actual_distance_to_destination
actual_time \
133488                 3159.0                1518.025696
2492.0

      osrm_time  osrm_distance  segment_actual_time
segment_osrm_time \
133488      1400.0        1931.1737                54.0
21.0

      segment_osrm_distance
133488             21.5097

dd.shape

(144867, 19)

#checking the unique values for columns
for _ in dd.columns:
    print()
    print(f'Total Unique Values in {_} column are :-\n{dd[_].nunique()}')
    print(f'Unique Values in {_} column are :-\n{dd[_].unique()}')
    print()
    print('*'*120)

Total Unique Values in data column are :- 2
Unique Values in data column are :-
['training' 'test']

-----
-----
```



```

Total Unique Values in trip_creation_time column are :- 14817
Unique Values in trip_creation_time column are :-
['2018-09-20 02:35:36.476840' '2018-09-23 06:42:06.021680'
 '2018-09-14 15:42:46.437249' ... '2018-09-22 11:30:41.399439'
 '2018-09-17 11:35:28.838714' '2018-09-20 16:24:28.436231']
```

```
-----  
Total Unique Values in route_schedule_uuid column are :- 1504  
Unique Values in route_schedule_uuid column are :-  
['thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3297ef'  
'thanos::sroute:ff52ef7a-4d0d-4063-9bfe-cc211728881b'  
'thanos::sroute:a16bfa03-3462-4bce-9c82-5784c7d315e6' ...  
'thanos::sroute:72cf9feb-f4e3-4a55-b92a-0b686ee8fabc'  
'thanos::sroute:5e08be79-8a4c-4a91-a514-5350403c0e31'  
'thanos::sroute:a3c30562-87e5-471c-9646-0ed49c150996']  
-----  
-----
```

```
-----  
Total Unique Values in route_type column are :- 2  
Unique Values in route_type column are :-  
['Carting' 'FTL']  
-----  
-----
```

```
-----  
Total Unique Values in trip_uuid column are :- 14817  
Unique Values in trip_uuid column are :-  
['trip-153741093647649320' 'trip-153768492602129387'  
'trip-153693976643699843' ... 'trip-153761584139918815'  
'trip-153718412883843340' 'trip-153746066843555182']  
-----  
-----
```

```
-----  
Total Unique Values in source_center column are :- 1508  
Unique Values in source_center column are :-  
['IND388121AAA' 'IND388620AAB' 'IND421302AAG' ... 'IND361335AAA'  
'IND562132AAC' 'IND639104AAB']  
-----  
-----
```

```
-----  
Total Unique Values in source_name column are :- 1498  
Unique Values in source_name column are :-  
['Anand_VUNagar_DC (Gujarat)' 'Khambhat_MotvdDPP_D (Gujarat)'  
'Bhiwandi_Mankoli_HB (Maharashtra)' ... 'Dwarka_StnRoad_DC (Gujarat)'  
'Bengaluru_Nelmngla_L (Karnataka)' 'Kulithalai_AnnaNGR_D (Tamil  
Nadu)']  
-----  
-----
```

```
-----  
Total Unique Values in destination_center column are :- 1481  
Unique Values in destination_center column are :-
```

```
['IND388620AAB' 'IND388320AAA' 'IND411033AAA' ... 'IND600004AAA'  
'IND134203AAA' 'IND400701AAA']
```

```
Total Unique Values in destination_name column are :- 1468  
Unique Values in destination_name column are :-  
['Khambhat_MotvdDPP_D (Gujarat)' 'Anand_Vaghasi_IP (Gujarat)'  
'Pune_Tathawde_H (Maharashtra)' ... 'Chennai_Mylapore (Tamil Nadu)'  
'Naraingarh_Ward2DPP_D (Haryana)' 'Mumbai_Ghansoli_DC (Maharashtra)']
```

```
Total Unique Values in od_start_time column are :- 26369  
Unique Values in od_start_time column are :-  
['2018-09-20 03:21:32.418600' '2018-09-20 04:47:45.236797'  
'2018-09-23 06:42:06.021680' ... '2018-09-22 11:30:41.399439'  
'2018-09-17 11:35:28.838714' '2018-09-20 16:24:28.436231']
```

```
Total Unique Values in od_end_time column are :- 26369  
Unique Values in od_end_time column are :-  
['2018-09-20 04:47:45.236797' '2018-09-20 06:36:55.627764'  
'2018-09-23 11:44:28.365845' ... '2018-09-22 21:45:05.128533'  
'2018-09-17 13:32:21.128357' '2018-09-20 23:32:09.618069']
```

```
Total Unique Values in start_scan_to_end_scan column are :- 1915  
Unique Values in start_scan_to_end_scan column are :-  
[ 86. 109. 302. ... 2476. 1161. 2949.]
```

```
Total Unique Values in actual_distance_to_destination column are :-  
144515  
Unique Values in actual_distance_to_destination column are :-  
[10.43566024 18.9368423 27.63727904 ... 66.16359134 73.68066734  
70.03901016]
```

```
Total Unique Values in actual_time column are :- 3182
```

```
Unique Values in actual_time column are :-  
[ 14. 24. 40. ... 3169. 3318. 2980.]
```

```
Total Unique Values in osrm_time column are :- 1531  
Unique Values in osrm_time column are :-  
[ 11. 20. 28. ... 1340. 1439. 1312.]
```

```
Total Unique Values in osrm_distance column are :- 138046  
Unique Values in osrm_distance column are :-  
[ 11.9653 21.7243 32.5395 ... 97.0933 111.2709 88.7319]
```

```
Total Unique Values in segment_actual_time column are :- 747  
Unique Values in segment_actual_time column are :-  
[ 1.400e+01 1.000e+01 1.600e+01 2.100e+01 6.000e+00 1.500e+01  
2.800e+01 2.600e+01 3.800e+01 3.700e+01 4.100e+01 2.300e+01  
4.600e+01 3.000e+01 5.000e+01 9.300e+01 6.200e+01 4.900e+01  
2.700e+01 3.500e+01 6.700e+01 2.000e+01 5.100e+01 9.400e+01  
1.900e+01 1.200e+01 1.800e+01 1.100e+01 2.000e+00 1.300e+01  
2.400e+01 5.700e+01 1.000e+00 0.000e+00 2.200e+01 2.500e+01  
4.500e+01 8.000e+00 3.600e+01 4.200e+01 4.400e+01 7.500e+01  
7.800e+01 2.900e+01 3.400e+01 3.200e+01 6.000e+01 4.300e+01  
7.900e+01 4.000e+01 6.900e+01 5.800e+01 5.200e+01 4.800e+01  
5.500e+01 5.400e+01 4.700e+01 9.000e+00 8.700e+01 1.700e+01  
6.800e+01 5.600e+01 3.300e+01 4.000e+00 5.300e+01 2.000e+02  
6.500e+01 3.100e+01 8.800e+01 7.000e+00 8.400e+01 8.200e+01  
3.900e+01 1.010e+02 1.900e+02 2.020e+02 9.700e+01 8.600e+01  
2.910e+02 1.620e+02 4.310e+02 1.060e+02 1.530e+02 8.900e+01  
7.300e+01 3.000e+00 1.360e+02 6.600e+01 6.300e+01 5.000e+00  
4.220e+02 7.600e+01 8.300e+01 1.230e+02 7.200e+01 1.320e+02  
6.850e+02 1.038e+03 6.100e+01 5.900e+01 1.710e+02 1.410e+02  
7.000e+01 7.700e+01 1.250e+02 9.200e+01 7.100e+01 6.400e+01  
1.040e+02 1.120e+02 9.000e+01 9.800e+01 3.030e+02 1.240e+02  
8.100e+01 1.730e+02 9.100e+01 2.200e+02 1.750e+02 2.920e+02  
1.170e+02 4.680e+02 6.940e+02 1.090e+02 1.300e+02 3.710e+02  
6.110e+02 -2.600e+01 1.480e+02 1.070e+02 5.040e+02 1.150e+02  
8.000e+01 1.790e+02 1.080e+02 9.600e+01 1.000e+02 8.500e+01  
4.930e+02 4.440e+02 4.240e+02 7.600e+02 1.030e+02 2.320e+02  
1.490e+02 2.050e+02 9.420e+02 1.270e+02 7.400e+01 1.660e+02  
9.500e+01 1.440e+02 2.220e+02 1.540e+02 1.210e+02 1.840e+02  
3.250e+02 1.020e+02 5.270e+02 1.110e+02 5.390e+02 1.590e+02  
5.860e+02 3.460e+02 1.180e+02 3.190e+02 2.690e+02 2.950e+02
```

6.580e+02	2.410e+02	2.960e+02	9.900e+01	1.160e+02	1.140e+02
1.520e+02	-2.100e+01	2.130e+02	1.050e+02	1.220e+02	1.670e+02
-5.000e+00	1.780e+02	1.136e+03	1.190e+02	1.820e+02	2.120e+02
2.930e+02	1.870e+02	1.350e+02	9.010e+02	1.600e+02	2.240e+02
2.790e+02	1.280e+02	6.370e+02	1.310e+02	1.340e+02	5.590e+02
1.580e+02	1.200e+02	5.580e+02	3.940e+02	2.280e+02	2.770e+02
2.040e+02	2.297e+03	1.630e+02	1.130e+02	5.700e+02	2.720e+02
1.510e+02	7.080e+02	1.380e+02	2.810e+02	8.330e+02	-1.000e+00
5.020e+02	1.100e+02	1.570e+02	1.650e+02	2.080e+02	1.910e+02
3.480e+02	1.500e+02	1.430e+02	2.430e+02	2.330e+02	1.470e+02
3.550e+02	1.370e+02	6.590e+02	2.620e+02	2.440e+02	6.200e+02
1.810e+02	1.560e+02	2.700e+02	1.420e+02	6.270e+02	2.480e+02
2.510e+02	1.770e+02	1.860e+02	1.390e+02	2.880e+02	2.530e+02
2.230e+02	1.400e+02	1.330e+02	2.150e+02	3.470e+02	3.560e+02
2.670e+02	1.720e+02	1.290e+02	6.800e+02	3.450e+02	1.450e+02
4.760e+02	3.300e+02	1.880e+02	3.950e+02	3.850e+02	7.190e+02
1.039e+03	5.510e+02	4.590e+02	4.890e+02	2.100e+02	4.740e+02
1.700e+02	9.900e+02	1.550e+02	2.170e+02	3.230e+02	4.850e+02
3.180e+02	1.690e+02	4.190e+02	6.360e+02	1.850e+02	1.260e+02
3.020e+02	6.350e+02	2.030e+02	1.980e+02	3.600e+02	2.090e+02
2.290e+02	7.430e+02	1.117e+03	3.790e+02	3.090e+02	2.500e+02
1.460e+02	2.780e+02	3.140e+02	1.760e+02	2.340e+02	6.300e+02
3.930e+02	1.890e+02	4.160e+02	4.610e+02	2.630e+02	2.380e+02
1.140e+03	4.210e+02	2.260e+02	2.760e+02	1.610e+02	2.060e+02
1.153e+03	4.270e+02	3.390e+02	8.410e+02	5.220e+02	2.140e+02
1.830e+02	4.490e+02	6.120e+02	1.017e+03	1.640e+02	2.160e+02
3.520e+02	4.140e+02	4.470e+02	6.710e+02	2.210e+02	3.800e+02
2.940e+02	2.070e+02	2.370e+02	3.900e+02	3.750e+02	2.010e+02
1.800e+02	1.847e+03	3.880e+02	9.430e+02	5.160e+02	9.930e+02
2.640e+02	5.150e+02	9.470e+02	6.700e+02	1.680e+02	4.280e+02
4.040e+02	3.980e+02	2.270e+02	2.890e+02	3.990e+02	7.320e+02
5.560e+02	5.980e+02	1.050e+03	2.350e+02	7.660e+02	4.920e+02
6.460e+02	3.120e+02	6.950e+02	2.580e+02	3.590e+02	2.360e+02
3.540e+02	6.010e+02	6.400e+02	6.410e+02	5.070e+02	3.720e+02
2.750e+02	5.180e+02	4.400e+02	2.390e+02	5.100e+02	1.716e+03
7.410e+02	9.370e+02	3.860e+02	2.180e+02	2.650e+02	2.820e+02
2.990e+02	1.990e+02	6.890e+02	6.870e+02	3.220e+02	4.460e+02
3.810e+02	4.950e+02	5.930e+02	2.300e+02	9.340e+02	1.143e+03
3.840e+02	9.940e+02	3.160e+02	8.770e+02	4.150e+02	1.086e+03
1.960e+02	8.790e+02	8.960e+02	6.600e+02	5.240e+02	3.360e+02
5.440e+02	3.380e+02	6.620e+02	7.050e+02	3.110e+02	2.680e+02
1.211e+03	5.630e+02	1.981e+03	6.670e+02	3.320e+02	2.310e+02
8.430e+02	8.220e+02	-5.800e+01	5.730e+02	3.000e+02	-2.110e+02
1.740e+02	6.440e+02	3.570e+02	2.190e+02	2.600e+02	1.940e+02
2.110e+02	2.450e+02	2.032e+03	2.860e+02	2.710e+02	4.200e+02
5.430e+02	3.200e+02	5.570e+02	4.320e+02	2.460e+02	5.010e+02
6.480e+02	3.690e+02	5.250e+02	3.920e+02	6.430e+02	7.570e+02
4.780e+02	7.670e+02	2.850e+02	2.250e+02	7.170e+02	1.970e+02
9.580e+02	5.890e+02	4.620e+02	4.050e+02	1.036e+03	6.560e+02

2.351e+03	4.520e+02	6.530e+02	2.740e+02	1.077e+03	5.210e+02
4.830e+02	3.370e+02	4.500e+02	2.610e+02	9.500e+02	6.830e+02
3.500e+02	2.400e+02	3.910e+02	9.910e+02	2.590e+02	2.281e+03
5.910e+02	1.083e+03	3.280e+02	1.124e+03	1.207e+03	3.640e+02
5.360e+02	4.330e+02	5.870e+02	4.510e+02	7.110e+02	2.550e+02
2.980e+02	-1.200e+01	8.500e+02	9.350e+02	2.660e+02	5.480e+02
4.900e+02	2.464e+03	3.650e+02	5.750e+02	6.420e+02	-3.600e+01
1.008e+03	7.800e+02	2.540e+02	1.950e+02	3.820e+02	6.250e+02
6.510e+02	4.770e+02	5.060e+02	6.180e+02	4.350e+02	6.690e+02
9.920e+02	6.470e+02	3.270e+02	9.180e+02	1.067e+03	4.720e+02
1.125e+03	7.370e+02	4.130e+02	1.046e+03	6.970e+02	6.390e+02
4.290e+02	5.850e+02	3.080e+02	3.780e+02	5.400e+02	4.670e+02
5.170e+02	8.690e+02	5.660e+02	2.520e+02	4.340e+02	3.510e+02
6.230e+02	3.060e+02	7.680e+02	4.110e+02	1.065e+03	-4.200e+01
5.110e+02	3.490e+02	5.340e+02	5.090e+02	4.560e+02	1.055e+03
2.490e+02	4.410e+02	-5.100e+01	9.020e+02	3.010e+02	3.350e+02
3.050e+02	9.530e+02	9.050e+02	6.650e+02	4.090e+02	4.980e+02
5.690e+02	5.670e+02	5.950e+02	5.740e+02	7.990e+02	3.130e+02
6.280e+02	4.600e+02	4.870e+02	1.630e+03	7.700e+02	2.120e+03
2.800e+02	4.750e+02	4.800e+02	6.020e+02	4.660e+02	3.530e+02
6.980e+02	1.131e+03	7.620e+02	7.180e+02	9.950e+02	8.090e+02
2.730e+02	3.340e+02	2.970e+02	4.640e+02	4.170e+02	-2.440e+02
6.000e+02	4.970e+02	8.140e+02	9.320e+02	8.700e+02	3.580e+02
1.097e+03	6.260e+02	3.680e+02	7.550e+02	1.061e+03	1.032e+03
4.230e+02	8.910e+02	3.240e+02	3.420e+02	6.820e+02	1.152e+03
5.880e+02	4.100e+02	9.680e+02	7.710e+02	3.290e+02	7.310e+02
-3.000e+00	9.590e+02	4.020e+02	1.166e+03	8.150e+02	4.960e+02
4.390e+02	9.160e+02	1.182e+03	8.490e+02	2.830e+02	8.940e+02
5.940e+02	5.280e+02	2.470e+02	2.900e+02	7.120e+02	1.041e+03
2.420e+02	1.128e+03	-7.400e+01	7.070e+02	6.290e+02	3.330e+02
5.600e+02	6.770e+02	6.100e+02	9.820e+02	1.920e+02	8.550e+02
3.610e+02	6.210e+02	6.740e+02	1.001e+03	9.610e+02	7.330e+02
6.880e+02	7.200e+02	3.310e+02	2.570e+02	2.408e+03	5.310e+02
1.025e+03	8.400e+02	1.584e+03	1.246e+03	7.470e+02	8.930e+02
6.310e+02	6.780e+02	4.010e+02	5.970e+02	9.270e+02	1.167e+03
1.115e+03	3.260e+02	7.150e+02	1.930e+02	1.395e+03	9.670e+02
5.370e+02	6.040e+02	3.210e+02	3.770e+02	8.510e+02	1.016e+03
1.031e+03	4.550e+02	6.220e+02	3.890e+02	5.830e+02	-4.800e+01
4.180e+02	1.047e+03	6.930e+02	9.700e+02	7.040e+02	7.850e+02
-2.000e+00	2.491e+03	9.460e+02	4.650e+02	2.541e+03	1.122e+03
3.051e+03	9.740e+02	9.780e+02	9.040e+02	-1.600e+01	8.530e+02
4.790e+02	1.148e+03	5.720e+02	4.250e+02	5.530e+02	4.060e+02
-7.000e+00	3.070e+02	1.093e+03	4.630e+02	9.390e+02	5.450e+02
1.325e+03	9.150e+02	5.460e+02	7.530e+02	5.290e+02	4.370e+02
5.200e+02	8.300e+02	1.677e+03	1.020e+03	7.480e+02	4.880e+02
6.130e+02	9.510e+02	3.740e+02	7.360e+02	9.330e+02	5.790e+02
2.625e+03	7.520e+02	-1.500e+01	1.192e+03	6.640e+02	1.320e+03
2.870e+02	3.700e+02	1.104e+03]			

```
-----  
-----  
Total Unique Values in segment_osrm_time column are :- 214  
Unique Values in segment_osrm_time column are :-  
[1.100e+01 9.000e+00 7.000e+00 1.200e+01 5.000e+00 6.000e+00  
1.000e+01  
2.400e+01 2.700e+01 2.600e+01 1.400e+01 1.500e+01 3.000e+01 1.800e+01  
3.800e+01 3.700e+01 2.500e+01 1.700e+01 2.200e+01 3.600e+01 3.200e+01  
1.600e+01 7.000e+01 3.500e+01 4.500e+01 1.300e+01 0.000e+00 8.000e+00  
2.000e+00 1.900e+01 2.300e+01 2.800e+01 2.000e+01 2.100e+01 3.300e+01  
3.400e+01 8.100e+01 3.000e+00 4.400e+01 1.000e+00 4.000e+00 3.900e+01  
4.000e+01 2.900e+01 5.300e+01 3.100e+01 7.500e+01 7.900e+01 9.700e+01  
4.800e+01 4.100e+01 4.300e+01 5.000e+01 5.400e+01 6.800e+01 4.200e+01  
4.600e+01 6.000e+01 5.800e+01 7.600e+01 4.900e+01 1.300e+02 7.800e+01  
6.700e+01 6.400e+01 5.500e+01 5.100e+01 1.420e+02 7.700e+01 7.100e+01  
5.600e+01 6.600e+01 5.900e+01 9.200e+01 6.200e+01 5.200e+01 5.700e+01  
8.000e+01 4.700e+01 7.400e+01 6.500e+01 8.800e+01 7.200e+01 6.900e+01  
7.300e+01 8.400e+01 8.200e+01 8.300e+01 1.540e+02 9.100e+01 6.100e+01  
9.400e+01 1.220e+02 6.300e+01 2.180e+02 9.800e+01 8.700e+01 3.830e+02  
9.000e+01 1.080e+02 9.300e+01 8.600e+01 8.900e+01 1.020e+02 1.600e+02  
2.210e+02 1.050e+02 1.330e+02 1.000e+02 1.060e+02 4.070e+02 8.500e+01  
1.340e+02 4.690e+02 1.800e+02 2.340e+02 1.490e+02 1.010e+02 1.450e+02  
1.140e+02 1.840e+02 2.270e+02 1.740e+02 1.320e+02 9.900e+01 9.600e+01  
1.310e+02 1.110e+02 1.040e+02 1.750e+02 2.300e+02 9.500e+01 1.250e+02  
2.950e+02 1.560e+02 1.160e+02 1.460e+02 1.410e+02 1.030e+02 1.170e+02  
2.310e+02 2.540e+02 2.200e+02 2.330e+02 1.810e+02 1.210e+02 1.270e+02  
3.700e+02 3.750e+02 1.500e+02 1.070e+02 1.610e+02 2.320e+02 1.090e+02  
1.200e+02 1.100e+02 9.970e+02 1.790e+02 1.130e+02 1.660e+02 9.960e+02  
1.240e+02 2.150e+02 1.570e+02 3.620e+02 1.430e+02 1.150e+02 1.280e+02  
1.700e+02 1.440e+02 2.350e+02 1.510e+02 3.560e+02 1.180e+02 1.390e+02  
1.710e+02 1.290e+02 1.190e+02 1.690e+02 1.630e+02 2.040e+02 1.480e+02  
1.830e+02 4.810e+02 3.410e+02 3.280e+02 2.130e+02 1.890e+02 1.910e+02  
1.400e+02 1.470e+02 2.080e+02 2.860e+02 2.160e+02 1.720e+02 1.380e+02  
1.670e+02 2.940e+02 1.230e+02 1.260e+02 2.110e+02 1.611e+03 2.190e+02  
2.490e+02 1.850e+02 1.580e+02 3.240e+02 1.770e+02 4.530e+02 1.520e+02  
1.760e+02 7.370e+02 1.730e+02 1.032e+03]  
-----  
-----
```

```
-----  
-----  
Total Unique Values in segment_osrm_distance column are :- 113799  
Unique Values in segment_osrm_distance column are :-  
[11.9653 9.759 10.8152 ... 20.7053 18.8885 8.8088]  
-----  
-----
```

** Changing the Datatype of Columns**

```
dd.sample()

          data      trip_creation_time \
124444  training  2018-09-23 02:44:13.665024

                                         route_schedule_uuid
route_type \
124444  thanos::sroute:f01c8bbd-655d-42ea-9abf-60d5040...      FTL

          trip_uuid source_center
source_name \
124444  trip-153767065366477819  IND821115AAB  Sasaram_Central_I_2
(Bihar)

          destination_center           destination_name \
124444        IND209304AAA  Kanpur_Central_H_6 (Uttar Pradesh)

          od_start_time          od_end_time \
124444  2018-09-23 17:32:37.941229  2018-09-24 04:42:20.756776

          start_scan_to_end_scan  actual_distance_to_destination
actual_time \
124444                  669.0                22.302481
27.0

          osrm_time  osrm_distance  segment_actual_time
segment_osrm_time \
124444       17.0          25.4394            27.0
17.0

          segment_osrm_distance
124444             25.4394

dd.dtypes

data                      object
trip_creation_time          object
route_schedule_uuid          object
route_type                   object
trip_uuid                    object
source_center                 object
source_name                   object
destination_center            object
destination_name              object
od_start_time                 object
od_end_time                   object
start_scan_to_end_scan       float64
actual_distance_to_destination float64
```

```

actual_time                      float64
osrm_time                        float64
osrm_distance                     float64
segment_actual_time               float64
segment_osrm_time                 float64
segment_osrm_distance              float64
dtype: object

# Converting the datatypes to category for columns like data and route_type as they only have 2 values.
dd['data'] = dd['data'].astype('category')
dd['route_type'] = dd['route_type'].astype('category')

# Converting time columns to datetime format
datetime_cols = ['trip_creation_time', 'od_start_time', 'od_end_time']
for _ in datetime_cols:
    dd[_] = pd.to_datetime(dd[_])

dd.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 19 columns):
 #   Column           Non-Null Count  Dtype  
 ---  --  
 0   data             144867 non-null   category
 1   trip_creation_time 144867 non-null   datetime64[ns]
 2   route_schedule_uuid 144867 non-null   object  
 3   route_type        144867 non-null   category
 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   datetime64[ns]
 10  od_end_time       144867 non-null   datetime64[ns]
 11  start_scan_to_end_scan 144867 non-null   float64
 12  actual_distance_to_destination 144867 non-null   float64
 13  actual_time        144867 non-null   float64
 14  osrm_time          144867 non-null   float64
 15  osrm_distance      144867 non-null   float64
 16  segment_actual_time 144867 non-null   float64
 17  segment_osrm_time   144867 non-null   float64
 18  segment_osrm_distance 144867 non-null   float64
dtypes: category(2), datetime64[ns](3), float64(8), object(6)
memory usage: 19.1+ MB

float_cols = []
for _ in dd.columns:
    if isinstance(dd[_], 'float64'):

```

```
        float_cols.append(_)
float_cols
```

see y it didnt work

```
float_cols = []
for _ in dd.columns:
    if dd[_].dtype=='float64':
        float_cols.append(_)
float_cols

['start_scan_to_end_scan',
 'actual_distance_to_destination',
 'actual_time',
 'osrm_time',
 'osrm_distance',
 'segment_actual_time',
 'segment_osrm_time',
 'segment_osrm_distance']

# reducing the float64 to float32 to save memory
for _ in float_cols:
    dd[_] = dd[_].astype('float32')

dd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 19 columns):
```

#	Column	Non-Null Count	Dtype
0	data	144867	non-null
1	trip_creation_time	144867	non-null
2	route_schedule_uuid	144867	non-null
3	route_type	144867	non-null
4	trip_uuid	144867	non-null
5	source_center	144867	non-null
6	source_name	144574	non-null
7	destination_center	144867	non-null
8	destination_name	144606	non-null
9	od_start_time	144867	non-null
10	od_end_time	144867	non-null
11	start_scan_to_end_scan	144867	non-null
12	actual_distance_to_destination	144867	non-null
13	actual_time	144867	non-null
14	osrm_time	144867	non-null
15	osrm_distance	144867	non-null
16	segment_actual_time	144867	non-null
17	segment_osrm_time	144867	non-null
18	segment_osrm_distance	144867	non-null

```
dtypes: category(2), datetime64[ns](3), float32(8), object(6)
memory usage: 14.6+ MB
```

Insights:

- Earlier the dataset was using 25.6+ MB of memory but now it has been reduced to 14.6 + MB. Around 40.63 % reduction in the memory usage.

```
# Time period of data
dd['trip_creation_time'].max(), dd['trip_creation_time'].min() ,
dd['trip_creation_time'].max()-dd['trip_creation_time'].min()

(Timestamp('2018-10-03 23:59:42.701692'),
 Timestamp('2018-09-12 00:00:16.535741'),
 Timedelta('21 days 23:59:26.165951'))

# Time period of data
dd['od_start_time'].max(), dd['od_start_time'].min(),
dd['od_start_time'].max() - dd['od_start_time'].min()

(Timestamp('2018-10-06 04:27:23.392375'),
 Timestamp('2018-09-12 00:00:16.535741'),
 Timedelta('24 days 04:27:06.856634'))

# Time period of data
dd['od_end_time'].max(), dd['od_end_time'].min(),
dd['od_end_time'].max() - dd['od_end_time'].min()

(Timestamp('2018-10-08 03:00:24.353479'),
 Timestamp('2018-09-12 00:50:10.814399'),
 Timedelta('26 days 02:10:13.539080'))

data_time_frame = dd['od_end_time'].max() -
dd['trip_creation_time'].min()
data_time_frame

Timedelta('26 days 03:00:07.817738')
```

Null Treatment:

Replace null values in 'source_name' and 'destination_name' columns with 'unknown' through scikit imputation

```
columns_to_impute = ['source_name', 'destination_name']
imputer = SimpleImputer(strategy='constant', fill_value='unknown')
dd[columns_to_impute] = imputer.fit_transform(dd[columns_to_impute])
```

but 'unknown' transactions will be more and to be omitted while analyzing ... Hence no use of imputing....

```
dd[(dd.source_name.isna())&(dd.destination_name.isna())]
```

	data	trip_creation_time	\
68006	training	2018-09-26 22:21:56.619259	
68007	training	2018-09-26 22:21:56.619259	
68008	training	2018-09-26 22:21:56.619259	
		route_schedule_uuid	route_type \
68006	thanos::sroute:cfb575b8-df26-48f5-8427-6f48f9d...		FTL
68007	thanos::sroute:cfb575b8-df26-48f5-8427-6f48f9d...		FTL
68008	thanos::sroute:cfb575b8-df26-48f5-8427-6f48f9d...		FTL
		trip_uuid	source_center source_name
destination_center	\		
68006	trip-153800051661903546	IND331022A1B	NaN
IND331001A1C			
68007	trip-153800051661903546	IND331022A1B	NaN
IND331001A1C			
68008	trip-153800051661903546	IND331022A1B	NaN
IND331001A1C			
	destination_name	od_start_time	
od_end_time	\		
68006		Nan 2018-09-27 03:19:14.797080	2018-09-27
05:28:00.922915			
68007		Nan 2018-09-27 03:19:14.797080	2018-09-27
05:28:00.922915			
68008		Nan 2018-09-27 03:19:14.797080	2018-09-27
05:28:00.922915			
	start_scan_to_end_scan	actual_distance_to_destination	
actual_time	\		
68006	128.0		25.178606
26.0			
68007	128.0		45.101166
114.0			
68008	128.0		50.844666
128.0			
	osrm_time	osrm_distance	segment_actual_time
segment_osrm_time	\		
68006	23.0	25.724600	26.0
23.0			
68007	44.0	54.611000	88.0
21.0			
68008	49.0	60.920502	13.0
4.0			
	segment_osrm_distance		
68006		25.724600	
68007		28.886299	
68008		6.309600	

```

dd[dd.source_name.isna()]

      data      trip_creation_time \
112  training 2018-09-25 08:53:04.377810
113  training 2018-09-25 08:53:04.377810
114  training 2018-09-25 08:53:04.377810
115  training 2018-09-25 08:53:04.377810
116  training 2018-09-25 08:53:04.377810
...
144484    ...  ...
144485    test 2018-10-03 09:06:06.690094
144486    test 2018-10-03 09:06:06.690094
144487    test 2018-10-03 09:06:06.690094
144488    test 2018-10-03 09:06:06.690094

                           route_schedule_uuid
route_type \
112  thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0... FTL
113  thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0... FTL
114  thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0... FTL
115  thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0... FTL
116  thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0... FTL
...
144484    ...  ...
144485  thanos::sroute:cbeff3b6a-79ea-4d5e-a215-b558a70... FTL
144486  thanos::sroute:cbeff3b6a-79ea-4d5e-a215-b558a70... FTL
144487  thanos::sroute:cbeff3b6a-79ea-4d5e-a215-b558a70... FTL
144488  thanos::sroute:cbeff3b6a-79ea-4d5e-a215-b558a70... FTL

                           trip_uuid source_center source_name
destination_center \
112  trip-153786558437756691  IND342902A1B      NaN
IND302014AAA
113  trip-153786558437756691  IND342902A1B      NaN
IND302014AAA
114  trip-153786558437756691  IND342902A1B      NaN
IND302014AAA
115  trip-153786558437756691  IND342902A1B      NaN
IND302014AAA
116  trip-153786558437756691  IND342902A1B      NaN

```

IND302014AAA
144484	trip-153855756668984584	IND282002AAD	NaN	
IND474003AAA				
144485	trip-153855756668984584	IND282002AAD	NaN	
IND474003AAA				
144486	trip-153855756668984584	IND282002AAD	NaN	
IND474003AAA				
144487	trip-153855756668984584	IND282002AAD	NaN	
IND474003AAA				
144488	trip-153855756668984584	IND282002AAD	NaN	
IND474003AAA				
destination_name od_start_time				
\				
112	Jaipur_Hub (Rajasthan)	2018-09-26 06:58:08.054001		
113	Jaipur_Hub (Rajasthan)	2018-09-26 06:58:08.054001		
114	Jaipur_Hub (Rajasthan)	2018-09-26 06:58:08.054001		
115	Jaipur_Hub (Rajasthan)	2018-09-26 06:58:08.054001		
116	Jaipur_Hub (Rajasthan)	2018-09-26 06:58:08.054001		
144484	Gwalior_HrihrNgr_I (Madhya Pradesh)	2018-10-03 17:34:21.835475		
144485	Gwalior_HrihrNgr_I (Madhya Pradesh)	2018-10-03 17:34:21.835475		
144486	Gwalior_HrihrNgr_I (Madhya Pradesh)	2018-10-03 17:34:21.835475		
144487	Gwalior_HrihrNgr_I (Madhya Pradesh)	2018-10-03 17:34:21.835475		
144488	Gwalior_HrihrNgr_I (Madhya Pradesh)	2018-10-03 17:34:21.835475		
od_end_time start_scan_to_end_scan \				
112	2018-09-26 15:54:14.280942		536.0	
113	2018-09-26 15:54:14.280942		536.0	
114	2018-09-26 15:54:14.280942		536.0	
115	2018-09-26 15:54:14.280942		536.0	
116	2018-09-26 15:54:14.280942		536.0	
144484	2018-10-03 22:10:43.366324		276.0	
144485	2018-10-03 22:10:43.366324		276.0	
144486	2018-10-03 22:10:43.366324		276.0	
144487	2018-10-03 22:10:43.366324		276.0	

144488	2018-10-03 22:10:43.366324		276.0
osrm_distance \	actual_distance_to_destination	actual_time	osrm_time
112	22.783440	48.0	34.0
37.774899			
113	46.071251	98.0	41.0
56.357498			
114	67.714996	127.0	58.0
80.481102			
115	88.149643	156.0	73.0
101.255600			
116	112.691978	212.0	92.0
127.986000			
...
...
144484	45.134384	62.0	45.0
47.773399			
144485	66.542267	86.0	71.0
71.954903			
144486	88.143959	116.0	114.0
112.694298			
144487	111.084419	173.0	123.0
134.194000			
144488	108.820946	181.0	123.0
121.359802			
	segment_actual_time	segment_osrm_time	segment_osrm_distance
112	48.0	34.0	37.774899
113	49.0	33.0	34.166100
114	29.0	17.0	24.123600
115	28.0	14.0	20.774599
116	55.0	18.0	26.730400
...
144484	34.0	23.0	23.660101
144485	23.0	25.0	24.181499
144486	30.0	43.0	40.739399
144487	57.0	45.0	46.921700
144488	8.0	4.0	6.510100

```
[293 rows x 19 columns]

dd[dd.destination_name.isna()]

      data      trip_creation_time \
110  training  2018-09-25 08:53:04.377810
111  training  2018-09-25 08:53:04.377810
982    test    2018-10-01 20:56:18.155260
983    test    2018-10-01 20:56:18.155260
4882  training  2018-09-24 07:18:06.087341
...
144478    test  2018-10-03 09:06:06.690094
144479    test  2018-10-03 09:06:06.690094
144480    test  2018-10-03 09:06:06.690094
144481    test  2018-10-03 09:06:06.690094
144482    test  2018-10-03 09:06:06.690094

                           route_schedule_uuid
route_type \
110  thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0... FTL
111  thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0... FTL
982  thanos::sroute:d0ebdacd-e09b-47d3-be77-c9c4a05... FTL
983  thanos::sroute:d0ebdacd-e09b-47d3-be77-c9c4a05... FTL
4882 thanos::sroute:2f43f11e-d3ba-4590-9355-82928e1... FTL
...
144478  thanos::sroute:cbeff3b6a-79ea-4d5e-a215-b558a70... FTL
144479  thanos::sroute:cbeff3b6a-79ea-4d5e-a215-b558a70... FTL
144480  thanos::sroute:cbeff3b6a-79ea-4d5e-a215-b558a70... FTL
144481  thanos::sroute:cbeff3b6a-79ea-4d5e-a215-b558a70... FTL
144482  thanos::sroute:cbeff3b6a-79ea-4d5e-a215-b558a70... FTL

      trip_uuid source_center \
110  trip-153786558437756691  IND342601AAA
111  trip-153786558437756691  IND342601AAA
982  trip-153842737815495661  IND573103AAA
983  trip-153842737815495661  IND573103AAA
4882 trip-153777348608709328  IND202001AAB
...
144478  trip-153855756668984584  IND000000ACB
```

144479	trip-153855756668984584	IND000000ACB
144480	trip-153855756668984584	IND000000ACB
144481	trip-153855756668984584	IND000000ACB
144482	trip-153855756668984584	IND000000ACB
		source_name destination_center \
110	Piparcity_BsstdDPP_D (Rajasthan)	IND342902A1B
111	Piparcity_BsstdDPP_D (Rajasthan)	IND342902A1B
982	Arsikere_HsnRdDPP_D (Karnataka)	IND577116AAA
983	Arsikere_HsnRdDPP_D (Karnataka)	IND577116AAA
4882	Aligarh_KhirByps_I (Uttar Pradesh)	IND282002AAD
		...
144478	Gurgaon_Bilaspur_HB (Haryana)	IND282002AAD
144479	Gurgaon_Bilaspur_HB (Haryana)	IND282002AAD
144480	Gurgaon_Bilaspur_HB (Haryana)	IND282002AAD
144481	Gurgaon_Bilaspur_HB (Haryana)	IND282002AAD
144482	Gurgaon_Bilaspur_HB (Haryana)	IND282002AAD
		...
	destination_name	od_start_time
od_end_time \		
110	NaN	2018-09-26 05:04:49.254901 2018-09-26
06:58:08.054001		
111	NaN	2018-09-26 05:04:49.254901 2018-09-26
06:58:08.054001		
982	NaN	2018-10-02 01:22:21.450243 2018-10-02
02:07:27.840862		
983	NaN	2018-10-02 01:22:21.450243 2018-10-02
02:07:27.840862		
4882	NaN	2018-09-24 15:02:13.760270 2018-09-24
18:49:23.454535		

144478	NaN	2018-10-03 09:06:06.690094 2018-10-03
17:34:21.835475		
144479	NaN	2018-10-03 09:06:06.690094 2018-10-03
17:34:21.835475		
144480	NaN	2018-10-03 09:06:06.690094 2018-10-03
17:34:21.835475		
144481	NaN	2018-10-03 09:06:06.690094 2018-10-03
17:34:21.835475		
144482	NaN	2018-10-03 09:06:06.690094 2018-10-03
17:34:21.835475		
	start_scan_to_end_scan	actual_distance_to_destination
actual_time \		
110	113.0	24.538214
58.0		
111	113.0	34.657707
110.0		
982	45.0	22.029638

21.0			
983	45.0		35.528961
36.0			
4882	227.0		22.193687
40.0			
...
...			
144478	508.0		89.773705
108.0			
144479	508.0		110.854080
138.0			
144480	508.0		132.514236
304.0			
144481	508.0		154.024567
337.0			
144482	508.0		159.222534
345.0			
osrm_time osrm_distance segment_actual_time			
segment_osrm_time \			
110	33.0	30.884501	58.0
33.0			
111	43.0	41.536098	52.0
10.0			
982	16.0	22.962999	21.0
16.0			
983	25.0	36.505001	15.0
9.0			
4882	26.0	28.981701	40.0
26.0			
...
...			
144478	70.0	99.409599	21.0
16.0			
144479	94.0	124.659798	30.0
24.0			
144480	119.0	147.229507	166.0
24.0			
144481	130.0	177.239395	33.0
27.0			
144482	136.0	182.447998	8.0
5.0			
segment_osrm_distance			
110		30.884501	
111		10.651700	
982		22.962999	
983		13.542000	
4882		28.981701	

```

...
144478          ...
144479          23.359501
144479          25.250200
144480          22.569700
144481          24.978399
144482          5.208600

[261 rows x 19 columns]

ddd = dd.copy()

missing_source_name = ddd.loc[ddd['source_name'].isnull(),
 'source_center'].unique()
missing_source_name

array(['IND342902A1B', 'IND577116AAA', 'IND282002AAD', 'IND465333A1B',
 'IND841301AAC', 'IND509103AAC', 'IND126116AAA', 'IND331022A1B',
 'IND505326AAB', 'IND852118A1B'], dtype=object)

missing_destination_name = ddd.loc[ddd['destination_name'].isnull(),
 'destination_center'].unique()
missing_destination_name

array(['IND342902A1B', 'IND577116AAA', 'IND282002AAD', 'IND465333A1B',
 'IND841301AAC', 'IND505326AAB', 'IND852118A1B', 'IND126116AAA',
 'IND509103AAC', 'IND221005A1A', 'IND250002AAC', 'IND331001A1C',
 'IND122015AAC'], dtype=object)

# checking if element of one np.array isin another np.array

#np.all(df.loc[df['source_name'].isnull(),
 'source_center'].isin(missing_destination_name))

np.in1d(missing_source_name, missing_destination_name).all()

False

for _ in missing_source_name:
    unique_source_name = ddd.loc[ddd['source_center'] == _, 'source_name'].unique()
    if pd.isna(unique_source_name):
        print("Source Center : ", _, " - " * 5, "Source Name : ", 'NA')
    else :
        print("Source Center : ", _, " - " * 5, "Source Name : ", unique_source_name)

Source Center : IND342902A1B ----- Source Name : NA
Source Center : IND577116AAA ----- Source Name : NA
Source Center : IND282002AAD ----- Source Name : NA
Source Center : IND465333A1B ----- Source Name : NA
Source Center : IND841301AAC ----- Source Name : NA
Source Center : IND509103AAC ----- Source Name : NA

```

```

Source Center : IND126116AAA ----- Source Name : NA
Source Center : IND331022A1B ----- Source Name : NA
Source Center : IND505326AAB ----- Source Name : NA
Source Center : IND852118A1B ----- Source Name : NA

for _ in missing_destination_name:
    unique_destination_name = ddd.loc[ddd['destination_center'] == _, 'destination_name'].unique()
    if pd.isna(unique_destination_name):
        print("Destination Center :", _, "-" * 5, "Destination Name :", 'NA')
    else :
        print("Destination Center :", _, "-" * 5, "Destination Name :", unique_destination_name)

Destination Center : IND342902A1B ----- Destination Name : NA
Destination Center : IND577116AAA ----- Destination Name : NA
Destination Center : IND282002AAD ----- Destination Name : NA
Destination Center : IND465333A1B ----- Destination Name : NA
Destination Center : IND841301AAC ----- Destination Name : NA
Destination Center : IND505326AAB ----- Destination Name : NA
Destination Center : IND852118A1B ----- Destination Name : NA
Destination Center : IND126116AAA ----- Destination Name : NA
Destination Center : IND509103AAC ----- Destination Name : NA
Destination Center : IND221005A1A ----- Destination Name : NA
Destination Center : IND250002AAC ----- Destination Name : NA
Destination Center : IND331001A1C ----- Destination Name : NA
Destination Center : IND122015AAC ----- Destination Name : NA

count = 1
for i in missing_destination_name:
    ddd.loc[ddd['destination_center'] == i, 'destination_name'] = ddd.loc[ddd['destination_center'] == i, 'destination_name'].replace(np.nan, f'location_{count}')
    count += 1

d = {}
for i in missing_source_name:
    d[i] = ddd.loc[ddd['destination_center'] == i, 'destination_name'].unique()
for idx, val in d.items():
    if len(val) == 0:
        d[idx] = [f'location_{count}']
        count += 1
d2 = {}
for idx, val in d.items():
    d2[idx] = val[0]
for i, v in d2.items():
    print(i, v)

```

```

IND342902A1B location_1
IND577116AAA location_2
IND282002AAD location_3
IND465333A1B location_4
IND841301AAC location_5
IND509103AAC location_9
IND126116AAA location_8
IND331022A1B location_14
IND505326AAB location_6
IND852118A1B location_7

for i in missing_source_name:
    ddd.loc[ddd['source_center'] == i, 'source_name'] =
    ddd.loc[ddd['source_center'] == i, 'source_name'].replace(np.nan,
d2[i])

ddd.source_name.value_counts()

source_name
Gurgaon_Bilaspur_HB (Haryana)      23347
Bangalore_Nelmngla_H (Karnataka)   9975
Bhiwandi_Mankoli_HB (Maharashtra)  9088
Pune_Tathawde_H (Maharashtra)       4061
Hyderabad_Shamshbd_H (Telangana)   3340
...
Badkulla_Central_DPP_1 (West Bengal) 1
Kasganj_BnkrGate_D (Uttar Pradesh)  1
Shahjhnpur_NavdaCln_D (Uttar Pradesh) 1
Jaunpur_Katghara_D (Uttar Pradesh)  1
Krishnanagar_AnadiDPP_D (West Bengal) 1
Name: count, Length: 1508, dtype: int64

ddd.destination_name.value_counts()

destination_name
Gurgaon_Bilaspur_HB (Haryana)      15192
Bangalore_Nelmngla_H (Karnataka)   11019
Bhiwandi_Mankoli_HB (Maharashtra)  5492
Hyderabad_Shamshbd_H (Telangana)   5142
Kolkata_Dankuni_HB (West Bengal)   4892
...
Vijayawada (Andhra Pradesh)         1
Ranaghat_ArickDPP_D (West Bengal)  1
Mumbai_Sanpada_CP (Maharashtra)    1
Delhi_Lajwanti (Delhi)             1
Luxettipet_ShivaDPP_D (Telangana)  1
Name: count, Length: 1481, dtype: int64

```

even if we replace these nulls with some values, those are not gonna have any impact on the data.... so we can drop it as well..

```

261+290
551
len(delhivery_data)
144867
144867 - 551
144316
df = dd.dropna()
df.isna().sum().any()
False
df.info()

<class 'pandas.core.frame.DataFrame'>
Index: 144316 entries, 0 to 144866
Data columns (total 19 columns):
 #   Column           Non-Null Count   Dtype  
 ---  -- 
 0   data             144316 non-null    category
 1   trip_creation_time 144316 non-null    datetime64[ns]
 2   route_schedule_uuid 144316 non-null    object  
 3   route_type         144316 non-null    category
 4   trip_uuid          144316 non-null    object  
 5   source_center       144316 non-null    object  
 6   source_name         144316 non-null    object  
 7   destination_center 144316 non-null    object  
 8   destination_name    144316 non-null    object  
 9   od_start_time       144316 non-null    datetime64[ns]
 10  od_end_time        144316 non-null    datetime64[ns]
 11  start_scan_to_end_scan 144316 non-null    float32
 12  actual_distance_to_destination 144316 non-null    float32
 13  actual_time         144316 non-null    float32
 14  osrm_time           144316 non-null    float32
 15  osrm_distance        144316 non-null    float32
 16  segment_actual_time 144316 non-null    float32
 17  segment_osrm_time    144316 non-null    float32
 18  segment_osrm_distance 144316 non-null    float32
dtypes: category(2), datetime64[ns](3), float32(8), object(6)
memory usage: 15.7+ MB

```

Insights:

- Only two fields have a tiny fraction of missing values, less than 0.05% of the whole dataset.

- Since we have plenty of data to work with, we're choosing to just get rid of the missing values instead of trying to guess them using methods like using the average or most common value.
 - I'm dropping the missing values to keep things simple and not mess up how the features are spread out. But if a lot more data was missing, we could have used other methods like guessing based on what's there or using the most common values.
-

Exploratory Data Analysis

```

cp =
['gray', 'red', 'dimgrey', 'tomato', 'dimgray', 'orangered', 'k', 'salmon', 'gray',
'red', 'dimgrey', 'tomato', 'dimgray', 'orangered', 'k', 'salmon']

df.sample()

      data      trip_creation_time \
92389  training 2018-09-14 23:36:50.771430

                           route_schedule_uuid route_type \
92389 thanos::sroute:3f001d56-e933-4ba1-a7cf-26828f7...   Carting

                           trip_uuid source_center \
92389  trip-153696821077115152  IND515201AAA

                           source_name destination_center \
92389 Hindupur_Parigi_D (Andhra Pradesh)           IND515301AAA

                           destination_name
od_start_time \
92389  Madakasira_RTCStand_D (Andhra Pradesh) 2018-09-15
01:35:41.452946

                           od_end_time start_scan_to_end_scan \
92389 2018-09-15 02:46:18.759915                70.0

actual_distance_to_destination actual_time osrm_time
osrm_distance \
92389                      25.308775        51.0        21.0
30.9918

segment_actual_time segment_osrm_time
segment_osrm_distance \
92389              20.0                  5.0            8.1409

segment_key \
92389 trip-153696821077115152+IND515201AAA+IND515301AAA

segment_actual_time_sum segment_osrm_distance_sum \
92389                 50.0                  30.991899

```

```

    segment_osrm_time_sum
92389      20.0

plt.figure(figsize=(20,4))
plt.suptitle('Pie Percentage
distribution', fontsize=13, fontfamily='serif', fontweight='bold', backgroundcolor=cp[-1], color='w')

plt.subplot(141)
plt.pie(df['data'].value_counts(),
labels=df['data'].value_counts().index, colors=cp, counterclock=True ,
explode=(0.02,0.02) , autopct='%.2f%%', pctdistance=0.905,
textprops={'color':'k','fontsize':10} , shadow=True,
radius=1,wedgeprops=dict(edgecolor='r', linewidth=0.1, width=0.25))
plt.title('Data-
Pie', fontsize=10, fontfamily='serif', fontweight='bold', backgroundcolor=cp[0], color='w')

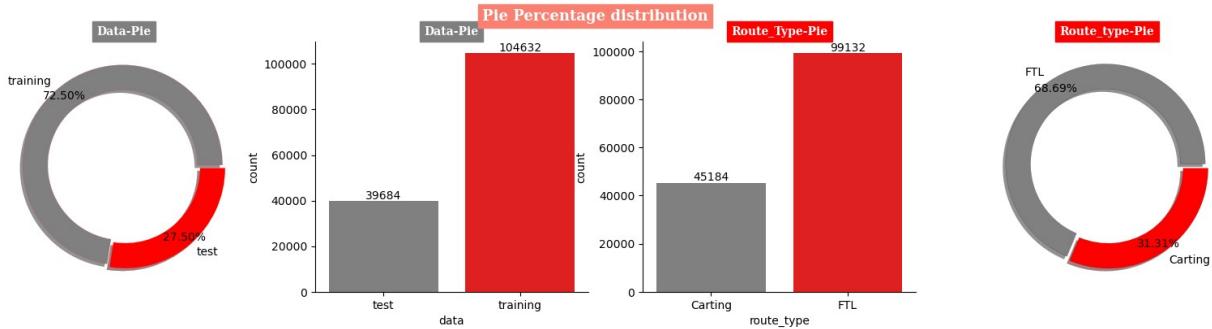
plt.subplot(142)
a = sns.barplot(x=df['data'].value_counts().index,
y=df['data'].value_counts(), palette=cp)
a.bar_label(a.containers[0], label_type='edge', fmt='%d')
plt.title('Data-
Pie', fontsize=10, fontfamily='serif', fontweight='bold', backgroundcolor=cp[0], color='w')

plt.subplot(143)
b = sns.barplot(x=df['route_type'].value_counts().index,
y=df['route_type'].value_counts(), palette=cp)
b.bar_label(b.containers[0], label_type='edge', fmt='%d')
plt.title('Route_Type-
Pie', fontsize=10, fontfamily='serif', fontweight='bold', backgroundcolor=cp[1], color='w')

plt.subplot(144)
plt.pie(df['route_type'].value_counts(),
labels=df['route_type'].value_counts().index,
colors=cp, counterclock=True , explode=(0.03,0.02) , autopct='%.2f%%',
pctdistance=0.905,
textprops={'color':'k','fontsize':10} , shadow=True,
radius=1,wedgeprops=dict(edgecolor='k', linewidth=0.1, width=0.25))
plt.title('Route_type-
Pie', fontsize=10, fontfamily='serif', fontweight='bold', backgroundcolor=cp[1], color='w')

sns.despine()
plt.show()

```



```

plt.figure(figsize=(25,13))
plt.style.use('default')
plt.style.use('seaborn-bright')

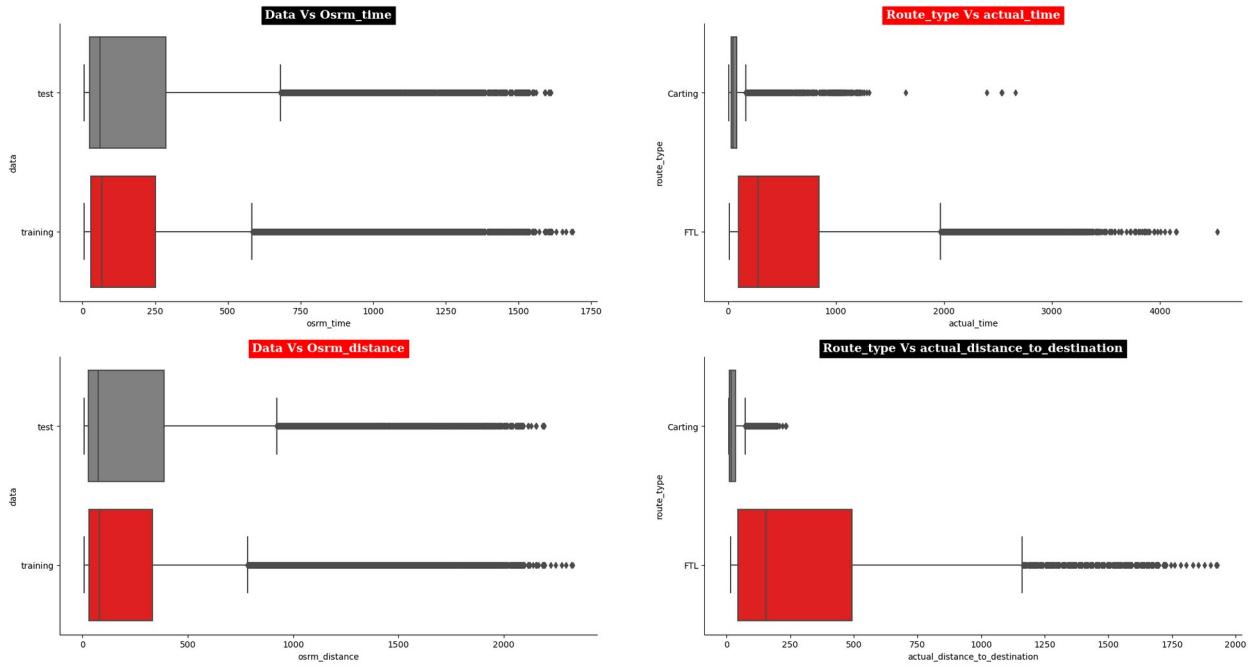
plt.subplot(221)
sns.boxplot(data=df,y='data',x='osrm_time',palette=cp)
plt.title('Data Vs  
Osrm_time',fontsize=14,fontfamily='serif',fontweight='bold',backgroundcolor='k',color='w')

plt.subplot(222)
sns.boxplot(data=df,y='route_type',x='actual_time',palette=cp)
plt.title('Route_type Vs  
actual_time',fontsize=14,fontfamily='serif',fontweight='bold',backgroundcolor='r',color='w')

plt.subplot(223)
sns.boxplot(data=df,y='data',x='osrm_distance',palette=cp)
plt.title('Data Vs  
Osrm_distance',fontsize=14,fontfamily='serif',fontweight='bold',backgroundcolor='r',color='w')

plt.subplot(224)
sns.boxplot(data=df,y='route_type',x='actual_distance_to_destination',palette=cp)
plt.title('Route_type Vs  
actual_distance_to_destination',fontsize=14,fontfamily='serif',fontweight='bold',backgroundcolor='k',color='w')
sns.despine()
plt.show()

```



Observations:

- Both training and test data have the same range of osrm time recorded
- FTL route type has more actual time compared to Carting. This can also be since FTL is used a lot more than carting in the data available to us
- Both training and test data have the same range of osrm distance recorded
- FTL route type has more actual distance compared to Carting. This can also be since FTL is used a lot more than carting in the data available to us

2. Merging of rows and aggregation of fields

Merging of rows and aggregation of fields

- Since delivery details of one package are divided into several rows (think of it as connecting flights to reach a particular destination). Now think about how we should treat their fields if we combine these rows? What aggregation would make sense if we merge. What would happen to the numeric fields if we merge the rows.

```
# Grouping by segment
# Creating a unique identifier for each segment of a trip

segment_cols = ['segment_actual_time', 'segment_osrm_distance',
'segment_osrm_time']

df['segment_key'] = df['trip_uuid'] + '+' + df['source_center'] + '+'
+ df['destination_center']

for col in segment_cols:
    df[col + '_sum'] = df.groupby('segment_key')[col].cumsum()
```

```

df[['segment_key', 'segment_actual_time',
   'segment_actual_time_sum','segment_osrm_distance',
   'segment_osrm_distance_sum','segment_osrm_time',
   'segment_osrm_time_sum']]

      segment_key \
0    trip-153741093647649320+IND388121AAA+IND388620AAB
1    trip-153741093647649320+IND388121AAA+IND388620AAB
2    trip-153741093647649320+IND388121AAA+IND388620AAB
3    trip-153741093647649320+IND388121AAA+IND388620AAB
4    trip-153741093647649320+IND388121AAA+IND388620AAB
...
144862  trip-153746066843555182+IND131028AAB+IND000000ACB
144863  trip-153746066843555182+IND131028AAB+IND000000ACB
144864  trip-153746066843555182+IND131028AAB+IND000000ACB
144865  trip-153746066843555182+IND131028AAB+IND000000ACB
144866  trip-153746066843555182+IND131028AAB+IND000000ACB

      segment_actual_time  segment_actual_time_sum
segment_osrm_distance \
0                  14.0                14.0
11.965300
1                  10.0                24.0
9.759000
2                  16.0                40.0
10.815200
3                  21.0                61.0
13.022400
4                  6.0                 67.0
3.915300
...
...
144862            12.0                92.0
8.185800
144863            26.0               118.0
17.372499
144864            20.0               138.0
20.705299
144865            17.0               155.0
18.888500
144866            268.0              423.0
8.808800

      segment_osrm_distance_sum  segment_osrm_time
segment_osrm_time_sum
0                  11.965300            11.0
11.0
1                  21.724300            9.0
20.0

```

2	32.539497	7.0
27.0		
3	45.561897	12.0
39.0		
4	49.477200	5.0
44.0		
...
...		
144862	65.348701	12.0
94.0		
144863	82.721199	21.0
115.0		
144864	103.426498	34.0
149.0		
144865	122.315002	27.0
176.0		
144866	131.123795	9.0
185.0		

[144316 rows x 7 columns]

Aggregating at segment level & Creating a dictionary for aggregation at segment level

```
segment_dict = {
    'trip_uuid' : 'first',
    'data': 'first',
    'route_type': 'first',
    'trip_creation_time': 'first',
    'source_name': 'first',
    'destination_name': 'last',
    'od_start_time': 'first',
    'od_end_time': 'last',
    'start_scan_to_end_scan': 'first',
    'actual_distance_to_destination': 'last',
    'actual_time': 'last',
    'osrm_time': 'last',
    'osrm_distance': 'last',
    'segment_actual_time' : 'sum',
    'segment_osrm_time' : 'sum',
    'segment_osrm_distance' : 'sum',
    'segment_actual_time_sum': 'last',
    'segment_osrm_time_sum': 'last',
    'segment_osrm_distance_sum': 'last',
}
```

Grouping by segment_key and aggregating

```
segment_agg_data =
df.groupby('segment_key').agg(segment_dict).reset_index()
segment_agg_data =
```

```

segment_agg_data.sort_values(by=['segment_key', 'od_end_time'])
segment_agg_data

    segment_key \
0  trip-153671041653548748+IND209304AAA+IND000000ACB
1  trip-153671041653548748+IND462022AAA+IND209304AAA
2  trip-153671042288605164+IND561203AAB+IND562101AAA
3  trip-153671042288605164+IND572101AAA+IND561203AAB
4  trip-153671043369099517+IND000000ACB+IND160002AAC
...
26217  trip-153861115439069069+IND628204AAA+IND627657AAA
26218  trip-153861115439069069+IND628613AAA+IND627005AAA
26219  trip-153861115439069069+IND628801AAA+IND628204AAA
26220  trip-153861118270144424+IND583119AAA+IND583101AAA
26221  trip-153861118270144424+IND583201AAA+IND583119AAA

        trip_uuid      data route_type \
0  trip-153671041653548748  training      FTL
1  trip-153671041653548748  training      FTL
2  trip-153671042288605164  training   Carting
3  trip-153671042288605164  training   Carting
4  trip-153671043369099517  training      FTL
...
26217  trip-153861115439069069      test   Carting
26218  trip-153861115439069069      test   Carting
26219  trip-153861115439069069      test   Carting
26220  trip-153861118270144424      test      FTL
26221  trip-153861118270144424      test      FTL

        trip_creation_time
source_name \
0  2018-09-12 00:00:16.535741  Kanpur_Central_H_6 (Uttar Pradesh)
1  2018-09-12 00:00:16.535741  Bhopal_Trnsport_H (Madhya Pradesh)
2  2018-09-12 00:00:22.886430  Doddablpur_ChikaDPP_D (Karnataka)
3  2018-09-12 00:00:22.886430          Tumkur_Veersagr_I (Karnataka)
4  2018-09-12 00:00:33.691250          Gurgaon_Bilaspur_HB (Haryana)
...
26217  2018-10-03 23:59:14.390954  Tirchchndr_Shnmgrpm_D (Tamil Nadu)
26218  2018-10-03 23:59:14.390954  Peikulam_SriVnktpm_D (Tamil Nadu)
26219  2018-10-03 23:59:14.390954          Eral_Busstand_D (Tamil Nadu)
26220  2018-10-03 23:59:42.701692          Sandur_WrdN1DPP_D (Karnataka)

```

26221 2018-10-03 23:59:42.701692

Hospet (Karnataka)

	destination_name	od_start_time
0	Gurgaon_Bilaspur_HB (Haryana)	2018-09-12 16:39:46.858469
1	Kanpur_Central_H_6 (Uttar Pradesh)	2018-09-12 00:00:16.535741
2	Chikblapur_ShntiSgr_D (Karnataka)	2018-09-12 02:03:09.655591
3	Doddablapur_ChikaDPP_D (Karnataka)	2018-09-12 00:00:22.886430
4	Chandigarh_Mehmdpur_H (Punjab)	2018-09-14 03:40:17.106733

...
26217	Thisayanvilai_UdnkdiRD_D (Tamil Nadu)	2018-10-04 02:29:04.272194
26218	Tirunelveli_VdkkuSrt_I (Tamil Nadu)	2018-10-04 04:16:39.894872
26219	Tirchchndr_Shnmgprm_D (Tamil Nadu)	2018-10-04 01:44:53.808000
26220	Bellary_Dc (Karnataka)	2018-10-04 03:58:40.726547
26221	Sandur_WrdN1DPP_D (Karnataka)	2018-10-04 02:51:44.712656

	od_end_time	start_scan_to_end_scan
0	2018-09-13 13:40:23.123744	1260.0
1	2018-09-12 16:39:46.858469	999.0
2	2018-09-12 03:01:59.598855	58.0
3	2018-09-12 02:03:09.655591	122.0
4	2018-09-14 17:34:55.442454	834.0

...

26217	2018-10-04 03:31:11.183797	62.0
26218	2018-10-04 05:47:45.162682	91.0
26219	2018-10-04 02:29:04.272194	44.0
26220	2018-10-04 08:46:09.166940	287.0
26221	2018-10-04 03:58:40.726547	66.0

osrm_distance	actual_distance_to_destination	actual_time	osrm_time
0	383.759155	732.0	329.0
446.549591			
1	440.973694	830.0	388.0
544.802673			
2	24.644020	47.0	26.0
28.199400			
3	48.542889	96.0	42.0

56.911598			
4	237.439606	611.0	212.0
281.210907			
...
...			
26217	33.627182	51.0	41.0
42.521301			
26218	33.673836	90.0	48.0
40.608002			
26219	12.661944	30.0	14.0
16.018499			
26220	40.546738	233.0	42.0
52.530300			
26221	25.534794	42.0	26.0
28.048401			
segment_actual_time segment_osrm_time			
segment_osrm_distance \			
0	728.0	534.0	670.620483
1	820.0	474.0	649.852783
2	46.0	26.0	28.199501
3	95.0	39.0	55.989899
4	608.0	231.0	317.740784
...
26217	49.0	42.0	42.143101
26218	89.0	77.0	78.586899
26219	29.0	14.0	16.018400
26220	233.0	42.0	52.530300
26221	41.0	25.0	28.048401
segment_actual_time_sum segment_osrm_time_sum \			
0	728.0	534.0	
1	820.0	474.0	
2	46.0	26.0	
3	95.0	39.0	
4	608.0	231.0	
...	
26217	49.0	42.0	
26218	89.0	77.0	

	segment_osrm_distance_sum	
0	670.620483	
1	649.852783	
2	28.199501	
3	55.989899	
4	317.740784	
...	...	
26217	42.143101	
26218	78.586899	
26219	16.018400	
26220	52.530300	
26221	28.048401	

[26222 rows x 20 columns]

Understanding:

The rows have been merged based on the unique segment_key, which is a combination of trip_uuid, source_center, and destination_center.

The aggregated dataset reflects the total values for each segment of the trip.

Feature Engineering

```
# 1. Calculating time difference between od_start_time and od_end_time
segment_agg_data['od_total_time']=(segment_agg_data['od_end_time'] - segment_agg_data['od_start_time'])
segment_agg_data['od_time_diff_hour'] =
(segment_agg_data['od_total_time']).dt.total_seconds()/3600
segment_agg_data
```

	segment_key \
0	trip-153671041653548748+IND209304AAA+IND000000ACB
1	trip-153671041653548748+IND462022AAA+IND209304AAA
2	trip-153671042288605164+IND561203AAB+IND562101AAA
3	trip-153671042288605164+IND572101AAA+IND561203AAB
4	trip-153671043369099517+IND000000ACB+IND160002AAC
..	..
26217	trip-153861115439069069+IND628204AAA+IND627657AAA
26218	trip-153861115439069069+IND628613AAA+IND627005AAA
26219	trip-153861115439069069+IND628801AAA+IND628204AAA
26220	trip-153861118270144424+IND583119AAA+IND583101AAA
26221	trip-153861118270144424+IND583201AAA+IND583119AAA

	trip_uuid \	data_route_type \
0	trip-153671041653548748	IND209304AAA
1	trip-153671041653548748	IND462022AAA
2	trip-153671042288605164	IND561203AAB
3	trip-153671042288605164	IND572101AAA
4	trip-153671043369099517	IND000000ACB
..
26217	trip-153861115439069069	IND628204AAA
26218	trip-153861115439069069	IND628613AAA
26219	trip-153861115439069069	IND628801AAA
26220	trip-153861118270144424	IND583119AAA
26221	trip-153861118270144424	IND583201AAA

	trip_id	type	status	...
0	trip-153671041653548748	training	FTL	...
1	trip-153671041653548748	training	FTL	...
2	trip-153671042288605164	training	Carting	...
3	trip-153671042288605164	training	Carting	...
4	trip-153671043369099517	training	FTL	...
...
26217	trip-153861115439069069	test	Carting	...
26218	trip-153861115439069069	test	Carting	...
26219	trip-153861115439069069	test	Carting	...
26220	trip-153861118270144424	test	FTL	...
26221	trip-153861118270144424	test	FTL	...
		trip_creation_time		
source_name \				
0	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)		...
1	2018-09-12 00:00:16.535741	Bhopal_Trnsport_H (Madhya Pradesh)		...
2	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)		...
3	2018-09-12 00:00:22.886430	Tumkur_Veersagr_I (Karnataka)		...
4	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)		...
...
26217	2018-10-03 23:59:14.390954	Tirchchndr_Shnmgrpm_D (Tamil Nadu)		...
26218	2018-10-03 23:59:14.390954	Peikulam_SriVnktpm_D (Tamil Nadu)		...
26219	2018-10-03 23:59:14.390954	Eral_Busstand_D (Tamil Nadu)		...
26220	2018-10-03 23:59:42.701692	Sandur_WrdN1DPP_D (Karnataka)		...
26221	2018-10-03 23:59:42.701692	Hospet (Karnataka)		...
		destination_name		
od_start_time \				
0	Gurgaon_Bilaspur_HB (Haryana) 2018-09-12 16:39:46.858469			...
1	Kanpur_Central_H_6 (Uttar Pradesh) 2018-09-12 00:00:16.535741			...
2	Chikblapur_ShntiSgr_D (Karnataka) 2018-09-12 02:03:09.655591			...
3	Doddablpur_ChikaDPP_D (Karnataka) 2018-09-12 00:00:22.886430			...
4	Chandigarh_Mehmdpur_H (Punjab) 2018-09-14 03:40:17.106733			...
...

```

.
26217 Thisayanvilai_UdnkdiRD_D (Tamil Nadu) 2018-10-04
02:29:04.272194
26218 Tirunelveli_VdkkuSrt_I (Tamil Nadu) 2018-10-04
04:16:39.894872
26219 Tirchchndr_Shnmgprm_D (Tamil Nadu) 2018-10-04
01:44:53.808000
26220 Bellary_Dc (Karnataka) 2018-10-04
03:58:40.726547
26221 Sandur_WrdN1DPP_D (Karnataka) 2018-10-04
02:51:44.712656

```

	od_end_time	start_scan_to_end_scan	\
0	2018-09-13 13:40:23.123744	1260.0	
1	2018-09-12 16:39:46.858469	999.0	
2	2018-09-12 03:01:59.598855	58.0	
3	2018-09-12 02:03:09.655591	122.0	
4	2018-09-14 17:34:55.442454	834.0	
...	
26217	2018-10-04 03:31:11.183797	62.0	
26218	2018-10-04 05:47:45.162682	91.0	
26219	2018-10-04 02:29:04.272194	44.0	
26220	2018-10-04 08:46:09.166940	287.0	
26221	2018-10-04 03:58:40.726547	66.0	

osrm_distance \	actual_distance_to_destination	actual_time	osrm_time
0	383.759155	732.0	329.0
446.549591			
1	440.973694	830.0	388.0
544.802673			
2	24.644020	47.0	26.0
28.199400			
3	48.542889	96.0	42.0
56.911598			
4	237.439606	611.0	212.0
281.210907			
...
...			
26217	33.627182	51.0	41.0
42.521301			
26218	33.673836	90.0	48.0
40.608002			
26219	12.661944	30.0	14.0
16.018499			
26220	40.546738	233.0	42.0
52.530300			
26221	25.534794	42.0	26.0
28.048401			

	segment_actual_time	segment_osrm_time	
segment_osrm_distance \			
0	728.0	534.0	670.620483
1	820.0	474.0	649.852783
2	46.0	26.0	28.199501
3	95.0	39.0	55.989899
4	608.0	231.0	317.740784
...
26217	49.0	42.0	42.143101
26218	89.0	77.0	78.586899
26219	29.0	14.0	16.018400
26220	233.0	42.0	52.530300
26221	41.0	25.0	28.048401
	segment_actual_time_sum	segment_osrm_time_sum \	
0	728.0	534.0	
1	820.0	474.0	
2	46.0	26.0	
3	95.0	39.0	
4	608.0	231.0	
...	
26217	49.0	42.0	
26218	89.0	77.0	
26219	29.0	14.0	
26220	233.0	42.0	
26221	41.0	25.0	
	segment_osrm_distance_sum	od_total_time	
od_time_diff_hour			
0	670.620483	0 days 21:00:36.265275	
21.010074	649.852783	0 days 16:39:30.322728	
16.658423	28.199501	0 days 00:58:49.943264	
0.980540	55.989899	0 days 02:02:46.769161	
2.046325	317.740784	0 days 13:54:38.335721	
13.910649			

```
...
...
26217           42.143101 0 days 01:02:06.911603
1.035253
26218           78.586899 0 days 01:31:05.267810
1.518130
26219           16.018400 0 days 00:44:10.464194
0.736240
26220           52.530300 0 days 04:47:28.440393
4.791233
26221           28.048401 0 days 01:06:56.013891
1.115559

[26222 rows x 22 columns]

segment_agg_data.sample()

        segment_key \
4965 trip-153704666810685062+IND173025AAA+IND160002AAC

            trip_uuid      data route_type
trip_creation_time \
4965 trip-153704666810685062 training          FTL 2018-09-15
21:24:28.108007

            source_name \
4965 PaontSahib_Gurudwar_D (Himachal Pradesh)

            destination_name          od_start_time \
4965 Chandigarh_Mehmdpur_H (Punjab) 2018-09-16 09:10:26.756767

            od_end_time  start_scan_to_end_scan \
4965 2018-09-16 14:11:04.351703             300.0

            actual_distance_to_destination  actual_time  osrm_time
osrm_distance \
4965                      85.146751          198.0       100.0
106.438904

            segment_actual_time  segment_osrm_time  segment_osrm_distance \
4965                  197.0                 99.0            121.251198

            segment_actual_time_sum  segment_osrm_time_sum \
4965                  197.0                 99.0

            segment_osrm_distance_sum          od_total_time
od_time_diff_hour
4965                  121.251198 0 days 05:00:37.594936
5.010443
```

```

# de =
segment_agg_data.drop(columns=['source_city', 'source_state', 'source_place', 'destination_place', 'destination_city', 'destination_state'])
de = segment_agg_data.copy()

de.sample()

                                segment_key \
4962  trip-153704666399260818+IND421302AAG+IND401104AAA

                           trip_uuid      data route_type
trip_creation_time \
4962  trip-153704666399260818  training   Carting 2018-09-15
21:24:23.992906

                           source_name
destination_name \
4962  Bhiwandi_Mankoli_HB (Maharashtra)  Mumbai_MiraRd_IP
(Maharashtra)

                           od_start_time          od_end_time \
4962  2018-09-15 21:24:23.992906  2018-09-16 01:16:04.776133

                           start_scan_to_end_scan  actual_distance_to_destination
actual_time \
4962                  231.0                      16.74782
102.0

                           osrm_time  osrm_distance  segment_actual_time  segment_osrm_time
\
4962        26.0        29.297199            102.0             25.0

                           segment_osrm_distance  segment_actual_time_sum
segment_osrm_time_sum \
4962                29.297199            102.0
25.0

                           segment_osrm_distance_sum          od_total_time
od_time_diff_hour
4962                  29.297199  0 days 03:51:40.783227
3.861329

# # could have done this --- but some major error ... check it....
# sad = segment_agg_data.copy()
# sad["source_city"] = sad["source_name"].str.split(
",n=1,expand=True)[0].str.split("_",n=1,expand=True)[0]
# sad["source_state"] = sad["source_name"].str.split(
",n=1,expand=True)[1].str.replace(",").str.replace(")", "")
# sad["destination_city"] = sad["destination_name"].str.split(
"
```

```

", n=1, expand=True)[0].str.split(" ", n=1, expand=True)[0]
# sad["destination_state"] = sad["destination_name"].str.split(
", n=1, expand=True)[1].str.replace("(, "")").str.replace(")", "")

# sad["source_place"] =
sad["source_name"].str.split("_", n=2, expand=True)[1]
# sad["destination_place"] =
sad["destination_name"].str.split("_", n=2, expand=True)[1]

# using regex pattern to seperate the city,place,state
def extract_info(name):
    pattern = r'^(?P<city>[^s_]+)_?(?P<place>[^(\)]*)\s?\((?P<state>[A-Za-z\s&]+)\)$'
    match = re.match(pattern, name)
    if match:
        city = match.group('city').strip()
        place = match.group('place').strip() if match.group('place')
    else city
        state = match.group('state').strip()
        return city, place, state
    else:
        return None, None, None

de[['source_city', 'source_place', 'source_state']] =
de['source_name'].apply(lambda x: pd.Series(extract_info(x)))

de[['destination_city', 'destination_place', 'destination_state']] =
de['destination_name'].apply(lambda x: pd.Series(extract_info(x)))

de


    segment_key \
0 trip-153671041653548748+IND209304AAA+IND000000ACB
1 trip-153671041653548748+IND462022AAA+IND209304AAA
2 trip-153671042288605164+IND561203AAB+IND562101AAA
3 trip-153671042288605164+IND572101AAA+IND561203AAB
4 trip-153671043369099517+IND000000ACB+IND160002AAC
...
26217 trip-153861115439069069+IND628204AAA+IND627657AAA
26218 trip-153861115439069069+IND628613AAA+IND627005AAA
26219 trip-153861115439069069+IND628801AAA+IND628204AAA
26220 trip-153861118270144424+IND583119AAA+IND583101AAA
26221 trip-153861118270144424+IND583201AAA+IND583119AAA



    trip_uuid      data route_type \
0 trip-153671041653548748 training      FTL
1 trip-153671041653548748 training      FTL
2 trip-153671042288605164 training   Carting
3 trip-153671042288605164 training   Carting
4 trip-153671043369099517 training      FTL
...


```

	trip_id	od_start_time	test	Carting
26217	trip-153861115439069069	2018-09-12 00:00:16.535741	test	Carting
26218	trip-153861115439069069	2018-09-12 00:00:16.535741	test	Carting
26219	trip-153861115439069069	2018-09-12 00:00:16.535741	test	Carting
26220	trip-153861118270144424	2018-09-12 00:00:22.886430	test	FTL
26221	trip-153861118270144424	2018-09-12 00:00:22.886430	test	FTL
		trip_creation_time		
	source_name \			
0	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)		
1	2018-09-12 00:00:16.535741	Bhopal_Trnsport_H (Madhya Pradesh)		
2	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)		
3	2018-09-12 00:00:22.886430	Tumkur_Veersagr_I (Karnataka)		
4	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)		
...
26217	2018-10-03 23:59:14.390954	Tirchchndr_Shnmgrpm_D (Tamil Nadu)		
26218	2018-10-03 23:59:14.390954	Peikulam_SriVnktpm_D (Tamil Nadu)		
26219	2018-10-03 23:59:14.390954	Eral_Busstand_D (Tamil Nadu)		
26220	2018-10-03 23:59:42.701692	Sandur_WrdN1DPP_D (Karnataka)		
26221	2018-10-03 23:59:42.701692	Hospet (Karnataka)		
		destination_name		
	od_start_time \			
0	Gurgaon_Bilaspur_HB (Haryana) 2018-09-12 16:39:46.858469			
1	Kanpur_Central_H_6 (Uttar Pradesh) 2018-09-12 00:00:16.535741			
2	Chikblapur_ShntiSgr_D (Karnataka) 2018-09-12 02:03:09.655591			
3	Doddablpur_ChikaDPP_D (Karnataka) 2018-09-12 00:00:22.886430			
4	Chandigarh_Mehmdpur_H (Punjab) 2018-09-14 03:40:17.106733			
...
26217	Thisayanvilai_UdnkdiRD_D (Tamil Nadu) 2018-10-04 02:29:04.272194			
26218	Tirunelveli_VdkkuSrt_I (Tamil Nadu) 2018-10-04 04:16:39.894872			
26219	Tirchchndr_Shnmgrpm_D (Tamil Nadu) 2018-10-04			

01:44:53.808000			
26220	Bellary_Dc (Karnataka)	2018-10-04	
03:58:40.726547			
26221	Sandur_WrdN1DPP_D (Karnataka)	2018-10-04	
02:51:44.712656			
	od_end_time	start_scan_to_end_scan	\
0	2018-09-13 13:40:23.123744	1260.0	
1	2018-09-12 16:39:46.858469	999.0	
2	2018-09-12 03:01:59.598855	58.0	
3	2018-09-12 02:03:09.655591	122.0	
4	2018-09-14 17:34:55.442454	834.0	
...	
26217	2018-10-04 03:31:11.183797	62.0	
26218	2018-10-04 05:47:45.162682	91.0	
26219	2018-10-04 02:29:04.272194	44.0	
26220	2018-10-04 08:46:09.166940	287.0	
26221	2018-10-04 03:58:40.726547	66.0	
	actual_distance_to_destination	actual_time	osrm_time
osrm_distance	\		
0	383.759155	732.0	329.0
446.549591			
1	440.973694	830.0	388.0
544.802673			
2	24.644020	47.0	26.0
28.199400			
3	48.542889	96.0	42.0
56.911598			
4	237.439606	611.0	212.0
281.210907			
...
...
26217	33.627182	51.0	41.0
42.521301			
26218	33.673836	90.0	48.0
40.608002			
26219	12.661944	30.0	14.0
16.018499			
26220	40.546738	233.0	42.0
52.530300			
26221	25.534794	42.0	26.0
28.048401			
	segment_actual_time	segment_osrm_time	
segment_osrm_distance	\		
0	728.0	534.0	670.620483
1	820.0	474.0	649.852783

2	46.0	26.0	28.199501
3	95.0	39.0	55.989899
4	608.0	231.0	317.740784
...
26217	49.0	42.0	42.143101
26218	89.0	77.0	78.586899
26219	29.0	14.0	16.018400
26220	233.0	42.0	52.530300
26221	41.0	25.0	28.048401

	segment_actual_time_sum	segment_osrm_time_sum	\
0	728.0	534.0	
1	820.0	474.0	
2	46.0	26.0	
3	95.0	39.0	
4	608.0	231.0	
...	
26217	49.0	42.0	
26218	89.0	77.0	
26219	29.0	14.0	
26220	233.0	42.0	
26221	41.0	25.0	
	segment_osrm_distance_sum	od_total_time	
od_time_diff_hour	\		
0	670.620483	0 days 21:00:36.265275	
21.010074			
1	649.852783	0 days 16:39:30.322728	
16.658423			
2	28.199501	0 days 00:58:49.943264	
0.980540			
3	55.989899	0 days 02:02:46.769161	
2.046325			
4	317.740784	0 days 13:54:38.335721	
13.910649			
...	
...			
26217	42.143101	0 days 01:02:06.911603	
1.035253			
26218	78.586899	0 days 01:31:05.267810	
1.518130			

```

26219          16.018400 0 days 00:44:10.464194
0.736240
26220          52.530300 0 days 04:47:28.440393
4.791233
26221          28.048401 0 days 01:06:56.013891
1.115559

      source_city source_place   source_state destination_city \
0           Kanpur  Central_H_6    Uttar Pradesh            Gurgaon
1           Bhopal   Trnsport_H  Madhya Pradesh            Kanpur
2        Doddablpur  ChikaDPP_D   Karnataka            Chikblapur
3           Tumkur  Veersagr_I   Karnataka            Doddablpur
4          Gurgaon  Bilaspur_HB   Haryana            Chandigarh
...
26217     Tirchchndr  Shnmgprm_D   Tamil Nadu  Thisayanvilai
26218     Peikulam  SriVnktpm_D   Tamil Nadu  Tirunelveli
26219       Eral    Busstand_D   Tamil Nadu  Tirchchndr
26220     Sandur   WrdN1DPP_D   Karnataka  Bellary
26221     Hospet          None    Karnataka  Sandur

      destination_place destination_state
0           Bilaspur_HB        Haryana
1           Central_H_6  Uttar Pradesh
2           ShntiSgr_D  Karnataka
3           ChikaDPP_D  Karnataka
4           Mehmdpur_H        Punjab
...
26217     UdnkdiRD_D  Tamil Nadu
26218     VdkkuSrt_I  Tamil Nadu
26219     Shnmgprm_D  Tamil Nadu
26220          Dc  Karnataka
26221     WrdN1DPP_D  Karnataka

[26222 rows x 28 columns]

de[(de['source_place']=='') | (de['destination_place']=='')]

      segment_key \
7  trip-153671052974046625+IND583101AAA+IND583201AAA
9  trip-153671052974046625+IND583201AAA+IND583119AAA
19  trip-153671110078355292+IND121004AAB+IND121001AAA
33  trip-153671173668736946+IND110043AAA+IND110078AAA
80  trip-153671320807895983+IND121004AAB+IND121102AAA
...
26118  trip-153860849934816308+IND110078AAA+IND110043AAA
26153  trip-153860958923357924+IND842003AAB+IND482002AAA
26180  trip-153861007249500192+IND842001AAA+IND846004AAA
26181  trip-153861007249500192+IND846004AAA+IND847103AAA
26221  trip-153861118270144424+IND583201AAA+IND583119AAA

```

	trip_uuid	data	route_type	\
7	trip-153671052974046625	training	FTL	
9	trip-153671052974046625	training	FTL	
19	trip-153671110078355292	training	Carting	
33	trip-153671173668736946	training	Carting	
80	trip-153671320807895983	training	Carting	
...
26118	trip-153860849934816308	test	Carting	
26153	trip-153860958923357924	test	Carting	
26180	trip-153861007249500192	test	FTL	
26181	trip-153861007249500192	test	FTL	
26221	trip-153861118270144424	test	FTL	
	trip_creation_time			
source_name	\			
7	2018-09-12 00:02:09.740725		Bellary_Dc	
(Karnataka)				
9	2018-09-12 00:02:09.740725		Hospet	
(Karnataka)				
19	2018-09-12 00:11:40.783923		FBD_Balabgarh_DPC	
(Haryana)				
33	2018-09-12 00:22:16.687619		Delhi_Nangli_IP	
(Delhi)				
80	2018-09-12 00:46:48.079257		FBD_Balabgarh_DPC	
(Haryana)				
...
.	.			
26118	2018-10-03 23:14:59.348414		Janakpuri	
(Delhi)				
26153	2018-10-03 23:33:09.233829	Jabalpur_Adhartal_IP	(Madhya Pradesh)	
26180	2018-10-03 23:41:12.495257		Muzaffarpur_Bbganj_I	
(Bihar)				
26181	2018-10-03 23:41:12.495257		Darbhanga	
(Bihar)				
26221	2018-10-03 23:59:42.701692		Hospet	
(Karnataka)				
	destination_name		od_start_time	\
7	Hospet (Karnataka)	2018-09-12 00:02:09.740725		
9	Sandur_WrdN1DPP_D (Karnataka)	2018-09-12 02:34:10.515593		
19	Faridabad (Haryana)	2018-09-12 00:11:40.783923		
33	Janakpuri (Delhi)	2018-09-12 00:22:16.687619		
80	Palwal (Haryana)	2018-09-12 00:46:48.079257		
...
26118	Delhi_Nangli_IP (Delhi)	2018-10-04 01:32:14.530264		
26153	Jabalpur (Madhya Pradesh)	2018-10-03 23:33:09.233829		
26180	Darbhanga (Bihar)	2018-10-03 23:41:12.495257		
26181	Benipur_Jawahar_D (Bihar)	2018-10-04 02:17:56.235080		

26221 Sandur_WrdN1DPP_D (Karnataka) 2018-10-04 02:51:44.712656

	od_end_time	start_scan_to_end_scan	\
7	2018-09-12 02:34:10.515593		152.0
9	2018-09-12 03:54:43.114421		80.0
19	2018-09-12 00:50:10.814399		38.0
33	2018-09-12 01:29:19.277412		67.0
80	2018-09-12 01:53:32.471405		66.0
...
26118	2018-10-04 03:05:32.479193		93.0
26153	2018-10-04 07:48:23.711056		495.0
26180	2018-10-04 02:17:56.235080		156.0
26181	2018-10-04 04:20:42.531207		122.0
26221	2018-10-04 03:58:40.726547		66.0

osrm_distance \	actual_distance_to_destination	actual_time	osrm_time
7	59.530350	147.0	46.0
63.646099			
9	26.600536	63.0	27.0
29.569599			
19	9.396525	17.0	9.0
10.815900			
33	12.756768	44.0	21.0
18.766800			
80	37.859165	45.0	28.0
39.724499			
...
...			
26118	12.207495	37.0	20.0
19.151501			
26153	9.065360	226.0	8.0
10.552100			
26180	53.236195	96.0	50.0
68.275101			
26181	24.323849	45.0	23.0
25.596600			
26221	25.534794	42.0	26.0
28.048401			

segment_osrm_distance \	segment_actual_time	segment_osrm_time	
7	147.0	45.0	63.646099
9	63.0	26.0	29.569698
19	17.0	9.0	10.815900
33	43.0	25.0	22.654800

80	44.0	27.0	39.724400
...
26118	37.0	24.0	18.512800
26153	226.0	8.0	10.552100
26180	95.0	49.0	68.275101
26181	45.0	23.0	25.596600
26221	41.0	25.0	28.048401
segment_actual_time_sum segment_osrm_time_sum \			
7	147.0	45.0	
9	63.0	26.0	
19	17.0	9.0	
33	43.0	25.0	
80	44.0	27.0	
...	
26118	37.0	24.0	
26153	226.0	8.0	
26180	95.0	49.0	
26181	45.0	23.0	
26221	41.0	25.0	
segment_osrm_distance_sum od_total_time			
od_time_diff_hour \			
7	63.646099	0 days 02:32:00.774868	
2.533549	29.569698	0 days 01:20:32.598828	
9	10.815900	0 days 00:38:30.030476	
1.342389	22.654800	0 days 01:07:02.589793	
19	39.724400	0 days 01:06:44.392148	
0.641675			
33			
1.117386			
80			
1.112331			
...	
...			
26118	18.512800	0 days 01:33:17.948929	
1.554986	10.552100	0 days 08:15:14.477227	
26153	68.275101	0 days 02:36:43.739823	
8.254021	25.596600	0 days 02:02:46.296127	
26180	2.612150		
26181			
2.046193			

```

26221          28.048401 0 days 01:06:56.013891
1.115559

      source_city    source_place    source_state destination_city \
7        Bellary           Dc       Karnataka      Hospet
9        Hospet
19        FBD   Balabhgarh_DPC     Haryana
33        Delhi      Nangli_IP     Delhi
80        FBD   Balabhgarh_DPC     Haryana
...        ...
26118    Janakpuri
26153    Jabalpur      Adhartal_IP  Madhya Pradesh
26180  Muzaffrpur      Bbganj_I      Bihar
26181  Darbhanga
26221    Hospet
                                         ...
destination_place destination_state
7
9        WrdN1DPP_D
19
33
80
...
26118      Nangli_IP
26153
26180
26181      Javahar_D
26221      WrdN1DPP_D
                                         ...
[782 rows x 28 columns]

de.loc[de['source_place']=='','source_place']=de['source_city']
de.loc[de['destination_place']=='','destination_place']=de['destination_city']

de[de.source_place.isna()]

Empty DataFrame
Columns: [segment_key, trip_uuid, data, route_type,
trip_creation_time, source_name, destination_name, od_start_time,
od_end_time, start_scan_to_end_scan, actual_distance_to_destination,
actual_time, osrm_time, osrm_distance, segment_actual_time,
segment_osrm_time, segment_osrm_distance, segment_actual_time_sum,
segment_osrm_time_sum, segment_osrm_distance_sum, od_total_time,
od_time_diff_hour, source_city, source_place, source_state,
destination_city, destination_place, destination_state]
Index: []

de.isna().sum()

```

```

segment_key          0
trip_uuid           0
data                0
route_type          0
trip_creation_time 0
source_name          0
destination_name    0
od_start_time       0
od_end_time         0
start_scan_to_end_scan 0
actual_distance_to_destination 0
actual_time          0
osrm_time            0
osrm_distance        0
segment_actual_time 0
segment_osrm_time   0
segment_osrm_distance 0
segment_actual_time_sum 0
segment_osrm_time_sum 0
segment_osrm_distance_sum 0
od_total_time        0
od_time_diff_hour   0
source_city          0
source_place          0
source_state          0
destination_city      0
destination_place     0
destination_state      0
dtype: int64

#de =
de.drop(columns=['source_city','source_state','source_place','destination_city', 'destination_place', 'destination_state'])

de.loc[de.source_city=='Bangalore','source_city']='Bengaluru'
de.loc[de.destination_city=='Bangalore','destination_city']='Bengaluru'

np.set_printoptions(threshold=np.inf)

de['source_city'].unique()

array(['Kanpur', 'Bhopal', 'Doddablpur', 'Tumkur', 'Gurgaon',
'Bengaluru',
'Mumbai', 'Bellary', 'Sandur', 'Hospet', 'Chennai', 'HBR',
'Surat',
'Delhi', 'Pune', 'FBD', 'Shirala', 'Ratnagiri', 'Kolhapur',
'Hyderabad', 'Anantapur', 'Thirumalagiri', 'Gulbarga', 'Aland',
'Sindagi', 'Indi', 'Jaipur', 'Allahabad', 'Guwahati', 'Unnao',
'Narsinghpur', 'Gadarwara', 'Shrirampur', 'Nashik', 'Sinnar'],

```

'Sangamner', 'Shirdi', 'Kopargaon', 'Vaijiapur', 'Hoogly',
'Hooghly', 'Kolkata', 'Madakasira', 'Pavagada', 'Sonari',
'Medchal', 'Dindigul', 'Kodaikanal', 'Batlagundu', 'Palani',
'Oddnchtram', 'Jalandhar', 'Nakodar', 'Kapurthala',
'Faridabad',
 'Chandigarh', 'Deoli', 'Pandharpur', 'Atapadi', 'CCU',
'Bhandara',
 'Kurnool', 'Palwal', 'Bhiwandi', 'Bhatinda', 'TalwandiSabo',
 'Mansa', 'Jhunir', 'RoopNagar', 'AnandprShb', 'Bantwal',
'Kadaba',
 'Sullia', 'Chittapur', 'Sedam', 'Chincholi', 'Lalru', 'Kadi',
 'Mehsana', 'Shahdol', 'Dola', 'Gangakher', 'Parli',
'Ambajogai',
 'Nanded', 'Loha', 'Durgapur', 'Bankura', 'Barjora', 'Vapi',
 'Jamjodhpur', 'Porbandar', 'Junagadh', 'Jetpur', 'Dhoraji',
 'Khammam', 'Nalgonda', 'Miryalguda', 'Suryapet', 'Choutuppal',
 'Vijayawada', 'Vadnagar', 'Palanpur', 'Deesa', 'Jabalpur',
 'Talala', 'Veraval', 'Una', 'Kodinar', 'Gundlupet',
'Tirumakudalu',
 'Chamarjngr', 'Malavalli', 'Kollegal', 'Mysore', 'Hunsur',
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 'GandhiRd_D', 'NJVNngr_D', 'GariDPP_D', 'barkarRd_D',
'GMukrDPP_D',
 'MP Nagar', 'Central_D_3', 'Jogshwri_I', 'GModDPP_D',
'KoilStrt_D',
 'CotnGren_M', 'Nzbadrd_D', 'Haridwar', 'Dwaraka_D',
'Devenply_I',
 'JKRoad_D', 'SuryaDPP_D', 'Menagrdn_D', 'NvygRDPP_D',
'CrossRD_D',
 'Sector1A_IP', 'PhrmPlza_D', 'Banikatt_D', 'Gndhichk_D',
'Dhelu_D',
 'Sulgwan_D', 'Bulabeda_D', 'Chowk_D', 'PatelNGR_D', 'Maheva_D',
 'BkgnRoad_D', 'CharRsta_D', 'Kollgpra_D', 'Peenya_IP',
 'GndhiNgr_IP', 'Sanpada_I', 'WrdN4DPP_D', 'Sakinaka_RP',
 'CivilHPL_D', 'OstwlEmp_D', 'KetyDPP_D', 'Gajuwaka',
'BaljiDPP_D',
 'Mhbhirab_D', 'CTRoad_D', 'MGRoad_D', 'RSRoad_D',
'Balajicly_I',
 'Artmclny_D', 'SDKNngr_D', 'Bngisheb_D', 'TirupthiRd_D',
 'BljiMrkt_D', 'DataSagr_D', 'Govndsgsgr_D', 'Dankuni_HB',
'Rakhial',
 'East_H_1', 'Memnagar', 'East_I_21', 'Mithakal_D',
'TrnspNgr_D',
 'Pakrela_D', 'Bbganj_I', 'Bilaspur_RP', 'Lovely_D',
'PatelWrd_D',
 'DivrsnRd_D', 'Mataward_D', 'CottonGreen_DPC', 'Pawane_L',
'Karur',
 'JPNagar_Pc', 'Knrpatti_D', 'Trchngrd_D', 'Kengeri_IP',
'KHRoad_I',
 'RicMilRd_D', 'MlnprDPP_D', 'MiraRd_IP', 'Pashan_DPC',
 'KhirByps_I', 'Agraroad_I', 'Katrmira_D', 'Sudmpuri_D',
'Potheri',

'Kuslpram_I', 'SamathBv_D', 'VadaiDPP_D', 'ColegRd_D',
'AmvdiDPP_D', 'HudcoDPP_D', 'Ward14_D', 'Nayapalli',
'Nirjanpur_L',
'Uppal_I', 'Jalukbari', 'Sardala_D', 'RPC', 'Chndivli_PC',
'AadiDPP_D', 'Banikhet_D', 'Bangotu_D', 'Chuanpur_I',
'RatanDPP_D',
'Hoodi_IP', 'Kadugodi_D', 'MhpраRD_D', 'AstrdDPP_D',
'Shop3DPP_D',
'Chikdply_I', 'Mayapuri_PC', 'Mylapore', 'GillChwk_DC',
'Anjur_C',
'Kishangarh_DPC', 'Janakpuri', 'Rohini_DPC', 'Panvel_D',
'MilrGanj_HB', 'Koliplm_I', 'Ghansoli_DC', 'Bhogal',
'KaaduRd_D',
'Patparganj_DPC', 'Salem', 'Mdhvpur_D', 'Hillcard_DC',
'WardNo3_D', 'Tiruchi', 'Sec_02_DPC', 'Sec-83_DC', 'Kadipur',
'Chukhndi_D', 'HosptlRd_D', 'Tetultol_D', 'Wardno5_D',
'HplrdDPP_D', 'Sraclepx_D', 'FoySGRRD_I', 'Nayagaon_I',
'Basni_I',
'SamitiRd_D', 'JawaharN_D', 'RoshnBgh_I', 'AmzonDev_V',
'Mundhawa_L', 'Vadgaon_Sheri_DPC', 'Alwal_L', 'LVMColge_D',
'GtRoad_D', 'HrihrNgr_I', 'Madaprum_D', 'Thmpulam_D',
'HnumnDPP_D',
'Raghogrh_D', 'Bypassrd_D', 'Truptingr_D', 'Faridabad',
'Peenya_L',
'Pandrnga_I', 'PunjabiB_L', 'Mdicalcly_D', 'CGRoad_D',
'Umalodge_D',
'Hejunagr_D', 'Wardno13_D', 'MahmurGj_IP', 'Adargchi_IP',
'NamoNagr_D', 'Bsavangr_D', 'Cdosclrd_D', 'GadagRD_D',
'Sector4_D',
'GndhiNGR_D', 'MChwkDPP_D', 'Govind_D', 'Parasi_D',
'Waidhan_D',
'Ward8DPP_D', 'PC', 'Central_I_2', 'SriDPP_D', 'SriRmNGR_D',
'Raiprvlg_L', 'MathuraRD_D', 'Panipat', 'kankroli_D',
'Nimachrd_D',
'Okhla_PC', 'Bownplly_C', 'Narynpur_C', 'Madhavaram_DPC',
'HUB',
'Chikdply_C', 'Markndpr_D', 'Udyabata_D', 'Sector02_C',
'Kuntikna_H', 'Kurduwdi_D', 'Kakdepot_D', 'Kothapet_D',
'SubhVRTL_I', 'Tiglgndi_D', 'Kacheri_D', 'BgwriDPP_D', 'CP',
'Vardhard_D', 'Vidygiri_D', 'Sanpada_CP', 'Egmore_C',
'Begumpur_CP', 'Sodal_Road', 'Ramvlg_D', 'Dehradun',
'MhmodNgr_D',
'Beleghtha_CP', 'MndiRoad_D', 'MohanNgr_C', 'Prbhunth_D',
'Soghra_D', 'PnditNGR_D', 'Madarpur_D', 'ChndrNgr_D',
'Robinson_D',
'Poothole_D', 'Peedika_H', 'Alandur_C', 'VaniThtr_D',
'BMRd_DC',
'Bburynkpl_D', 'Karelibaug_DPC', 'MhimWest_C', 'Malahi_D',
'Bgtichk_D', 'Vasai_CP', 'Mdhavram_C', 'Sector63_L',

'Karayam_H',
 'Sarubali_D', 'Sirjudin_D', 'YuktiDPP_D', 'IndstlAr_I',
'Nagar_DC',
 'ShivNgar_D', 'Katira_D', 'Sirikona_H', 'Jantaclg_D',
'Bankura_D',
 'Salanpur_D', 'Talkui_D', 'Jogeshwri_L', 'ZebaTWR_D',
'BhgyaNgr_D',
 'Mhdiptnm_C', 'North_R_8', 'Pratpngr_D', 'BSarani_D',
'NagarDPP_D',
 'MaxDPP_D', 'BtaiRoad_D', 'Kapskera_L', 'Chungam_D',
'HatRDDPP_D',
 'WdN14DPP_D', 'Egmore_DPC', 'Mangri_I', 'Atapaka_D',
'Agraharm_DC',
 'GvrCompx_D', 'ArhamDPP_D', 'DindiRD_D', 'PeroorRD_D',
 'VidyaNGR_D', 'GndhiDPP_D', 'Wazirpur_L', 'Alwal_I',
'SrifoDPP_D',
 'Kntgorya_D', 'DohalDPP_D', 'BoiDPP_D', 'NditaDPP_D',
 'Gajuwaka_IP', 'KrsprDPP_D', 'Sirjudol_D', 'GopalDPP_D',
 'UtBzrDPP_D', 'SavtaHTL_D', 'Hindcwk_D', 'MiraRoad_M',
 'GrmNgriya_D', 'ViksClny_D', 'kalibari_D', 'Konapara_D',
 'Indsarea_D', 'PlaceCol_D', 'Bhogpur_D', 'TahurDPP_D',
'Vijdurg_D',
 'Bardivan_D', 'Wardno6_D', 'Pinjore_DC', 'MohanPrk_D',
 'Thsil3PL_D', 'Gaurkshn_I', 'SChwkDPP_D', 'Mundhe_D',
'Shantanu_D',
 'LxmiNiws_D', 'ColctrOf_D', 'LSRoad_DC', 'SikriKla_DC',
'Meerut',
 'Krishnpr_D', 'SadrHsptl_D', 'Gangjala_D', 'Central_H_2',
 'Bazar_D', 'Wardn13_D', 'Durma_D', 'Ward9DPP_D', 'WardNo1_D',
 'IndraNgr_D', 'Enkndl_a_D', 'SrnavsNgr_D', 'RKComplx_D',
 'ShtDRDPP_D', 'VikrmMah_D', 'Rohtak', 'DvlalDPP_D',
'GainMrkt_L',
 'BsStdDPP_D', 'Darbhanga', 'Jawahar_D', 'Nagar_D', 'patna_D',
 'Vijayght_D', 'Shyndco_D', 'AgrohDPP_D', 'Gokulam_D',
'GVManu_D',
 'SaiNgr_D', 'Madnpali_D', 'Ambala', 'Gurudwar_D', 'Jhilmil_L',
 'BhukrdPP_D', 'Mwalibad_D', 'AjmhwdPP_D', 'Tilknagr_DC',
'Kumud_D',
 'Sookhtal_D', 'SuzkiSrv_D', 'Subhash_D', 'Barmasia_D',
 'NravnDPP_D', 'Nangli_L', 'Matriprom_IP', 'CCRoad_D',
'Subshngr_D',
 'BawliDPPP_D', 'Banjaria_D', 'Pchpkrd_D', 'BypassRd_D',
 'Trengard_D', 'Panderia_D', 'Dudhani_D', 'D', 'Hatpada_D',
 'Bhaleti_D', 'SainkSCL_D', 'Ward6_D', 'Dayanand_D',
'Fathuluh_D',
 'NaginaRd_D', 'NaginaRD_D', 'KotdwrrD_D', 'HunterRd_I',
 'Nrsampt_D', 'Perkadrd_D', 'KdidmCLY_D', 'Khwssrai_D',
'Ganesh_D',
 'Trimurti_D', 'Harop_D', 'KrsdhDPP_D', 'Ward2DPP_D',

'Vaishali_D',
 'BhwniGnj_D', 'BajprDPP_D', 'MubarDPP_D', 'BgnprDPP_D',
'RamNgr_D',
 'RajaBzr_D', 'Mohim_D', 'Datatrya_D', 'EBroad_D', 'Bidar',
 'RIICO_L', 'StatonRd_D', 'Shankrpaa_D', 'Verpatem_D',
'RailGate_D',
 'Kalol_DC', 'PODPP_D', 'MheshNGR_D', 'ITDARd_D', 'AskNagar_D',
 'SrnprHwy_D', 'DmodrNGR_D', 'IndraCln_D', 'NWclyDPP_D',
 'Ward6DPP_D', 'MndwrRod_D', 'HnsChowk_D', 'FatehpRd_I',
 'NavldiDPP_D', 'JdswarRD_D', 'Kalyanpr_D', 'KlngrDPP_D',
'NH117_D',
 'Antop_Hill', 'Pariplly_D', 'Rdiosttn_D', 'NrainaRD_D',
 'NarenaRD_D', 'ChomuRD_D', 'Sarswati_D', 'Nishangr_D',
 'NgrNigam_DC', 'Wardno4_D', 'Purbari_D', 'Pnjbiiyon_D',
'SJRoad_D',
 'DcntCLY_D', 'Kanongyn_D', 'Pettah_D', 'Arlumodu_D',
'MhraChng_D',
 'AryaNagr_D', 'Virar_DC', 'JNPT_D', 'Pbroad_DC', 'Goa',
 'ZuariNgr_IP', 'Mohan_Nagar_DPC', 'Swargash_D', 'HapurRD_D',
 'WardNo4_D', 'MnBzrDPP_D', 'GvrdnDPP_D', 'Kalyan_West_Dc',
 'Ambernath_Dc', 'ShivaDPP_D', 'GunjRDPP_D', 'Aravind_D',
 'Mumbra_DC', 'Hitech_D', 'KamnHbRD_I', 'UzanBazr_DC',
'TKRoad_D',
 'KeRoad_D', 'JatniDPP_D', 'Klskhrpt_D', 'PostofJN_D',
'Amankovl_D',
 'Town_D', 'MIDCAvdn_I', 'DhuleRoad_D', 'KakaCplx_D',
'Nandrbars_D',
 'DhuleRd_D', 'Dilliyan_D', 'Jaipur', 'Shahdara', 'DhnliRth_D',
 'Pdmavati_D', 'KhsmiDPP_D', 'Balaji_Nagar', 'BhadgDPP_D',
 'RamaNgr_D', 'Parigi_D', 'StatinRD_D', 'AdrshSt_DC',
'keshod_DC',
 'JilRDDPP_D', 'GayatriN_D', 'Kotwali_D', 'NehruNGR_D',
 'Arulimod_D', 'Ajnari_D', 'Madhavaram_L', 'GndhiNgr_D',
'Bokule_H',
 'JyotiNgr_D', 'BrlwgDPP_D', 'Selakui_D', 'Ward19_D',
'PalikDPP_D',
 'Nehru3PL_D', 'SttinDPP_D', 'FulbaDPP_D', 'Padra_D',
'CikhliRD_D',
 'StnRdDPP_D', 'Itachnda_D', 'WebelDPP_D', 'MilpaDPP_D',
 'Pshimpra_D', 'Uppal_L', 'BOB_D', 'Samarth_D', 'StRoad_D',
 'Tolichwk_I', 'Chndivli_D', 'Vadodara', 'Sholinganallur_Dc',
 'Sixmile', 'LB-Nagar_Dc', 'Panchkula', 'Bhgtpura_D',
'VishnuVhr_D',
 'ArkonmRD_D', 'MBTRd_DC', 'Sadras_D', 'Central_DPP_4',
'Chakan_D',
 'ColageRD_D', 'Srikot_D', 'Khajuria_I', 'ChrliDPP_D',
'SashPhkn_D',
 'ZoomCDPP_D', 'Shillong', 'ShanthiS_D', 'ShsmlDPP_D',
'KotwaliN_D',

'PBRDDPP_D', 'MduraiRD_D', 'LICoffce_D', 'Kaithwal_D',
'SmClyDPP_D', 'LXngrDPP_D', 'TrtllaRD_L', 'Blockrd_D',
'ManhrBld_D', 'Blmrgnst_D', 'StationRD_D', 'KrthiKyn_D',
'Satara_D', 'Idgah_P', 'Udupi', 'Kakrmath_D', 'KmkshBul_D',
'Prbhtngr_D', 'MarketRd_D', 'Mrdivlge_D', 'Ameenpur_I',
'Pazhvedu_D', 'Kumrpurm_D', 'Feroke_H', 'Mandodi_D',
'Pshrikvu_D',
'ZamQuatr_D', 'Mettu_DC', 'Thiruviz_D', 'Vadasari_D',
'Kdthdstrt_D', 'VaikLSRT_D', 'MukkuRD_D', 'Davisdle_D',
'nagar_D',
'Badeplly_D', 'anthniyr_D', 'HsptlRod_D', 'SH71_D',
'Puduvalvu_D',
'Sbrmnprm_D', 'Alngjuri_D', 'Sishumdr_D', 'PriyrNGR_D',
'Mthrapuri_D', 'ThryrRD_D', 'goplurm_D', 'Kmrajngr_D',
'Chithbrm_D', 'AmtladPP_D', 'JhumanCk_D', 'Kappalur_H',
'AshkTalk_D', 'Msstreet_DC', 'Krsnakcl_D', 'Kovil_D',
'Mlydpthr_D',
'Ward25_D', 'TherSRT_D', 'Kovaipudur_Dc', 'West_Dc',
'Khjurwli_DC',
'RtlamNka_D', 'Patiala', 'Sahni_D', 'MrutiNGR_D', 'Palikval_D',
'Talaiya_D', 'AshkngRd_D', 'Ward17_D', 'BhogdDPP_D', 'BMRd_D',
'MuruPost_D', 'MandyARD_D', 'MuthpTmp_D', 'TilakNgr_D',
'YTRd_D',
'HsnRdDPP_D', 'Anaipeta_D', 'GodamDPP_D', 'Ambedkar_D',
'Sunku_D',
'FshryOFC_D', 'KolarRd_D', 'Venkatsa_DC', 'Artclgrd_D',
'GuttalRD_D', 'War5DPP_D', 'HoliCDPP_D', 'KairiyaT_D',
'Wardno10_D', 'Techrcly_D', 'Thvrlsrt_D', 'Palladam_DC',
'Bhabua_D', 'Torwa_DC', 'HousngBd_D', 'New Alipore_DPC',
'Mutvila_D', 'Chnglptu_DC', 'Achipkam_D', 'Yellanda_D',
'Sudimala_D', 'VdkkuSrt_I', 'Radhaprm_D', 'Nallur_D',
'ChtrGIDC_IP', 'MrktYrd_DC', 'UdnkdiRD_D', 'Shnmgprm_D',
'SriVnktpm_D', 'SKRoad_D', 'VidyaNgr_D', 'PushPlza_D',
'Kalynpur_I', 'Kataram_D', 'JwahrNGR_D', 'LaxmiNGR_D',
'Darbe_DC',
'ConduDPP_D', 'JrjoldPP_D', 'Chandkheda_Dc', 'Chaitnya_D',
'MohnVRTL_D', 'JydevNGR_D', 'Civlline_D', 'ChngiDPP_D',
'Mlkpura_D', 'RjnndrNgr_DC', 'EtawahDPP_D', 'TBCross_D',
'ShntiSgr_D', 'Kalyan', 'GwhRDDPP_D', 'Vepmpttu_DC',
'TmpleSrt_D',
'Vllyaprm_D', 'RamnadRD_D', 'Raiprkln_C', 'Rawlgaon_D',
'Malegaon_D', 'Varachha_DC', 'South_D_4', 'VasaviNg_D',
'SnkunDPP_D', 'Shahapur_D', 'HBColny_D', 'Mangol_DC',
'KrisnKunj_D', 'Lake Avenue_DPC', 'NaturDPP_D', 'Kolar
Mandakni',
'Kadtmtpt_H', 'krshnPly_DC', 'EragnDPP_D', 'Tejpal_I',
'BjbNgr_DC',
'PndrgNgr_DC', 'Chandigarh', 'Mangalam_D', 'ShantiNg_D',
'Erode',

'DKLogDPP_D', 'Samrvrni_D', 'BaliaMod_D', 'Ganeshwr_D',
'NagplDPP_D', 'KisanCo_D', 'Palakrty_D', 'Hanmkond_D',
'BodomBzr_DC', 'RadhaCpx_D', 'MaladWest_CP', 'Mohnprwa_D',
'Mnanthla_D', 'ShjnprRD_D', 'Mainrd_D', 'Eaglvari_D',
'Kelasahi_D',
 'GhtimDPP_D', 'VallaDPP_D', 'TnhbBlkC_D', 'VagaiNgr_D',
 'LxmntDPP_D', 'KdrShrRd_D', 'Veluthur_D', 'AlathurRD_D',
 'KKndrDPP_D', 'SagarDPP_D', 'WamanDPP_D', 'SchdvDPP_D',
'LFRoad_D',
 'Rathnam_D', 'RgvdrDPP_D', 'HesglDPP_D', 'CroslySRT_D',
 'HajiprRD_D', 'Haripur_D', 'Srvdyckw_D', 'Tuminkte_D',
 'NharuExt_D', 'NngrgnRd_D', 'Valluvar_D', 'Banshkri_DC',
 'Mahindra_D', 'MrenTirh_D', 'NorprRD_D', 'Sitarmrd_D',
 'BaraLoha_D', 'Rajula_DC', 'KrantiNgr_D', 'ICDCant_D',
 'Greenmkt_D', 'Chandanagar_Dc', 'Mnanthla_H', 'BndhuTRH_D',
 'Chandmari', 'APMCYard_D', 'Barwala', 'Katora_IP',
'BasthDPP_D',
 'AsnsdhRD_D', 'MahuGDPP_D', 'SourvDPP_D', 'RPRoad_D',
'NagpurRd_D',
 'DelRdDPP_D', 'ward9_D', 'Central_D_5', 'Shekhpur_D',
'BypassRD_D',
 'MngalDPP_D', 'BhwanDPP_D', 'HghsclRD_D', 'Blbgarh_DC',
 'Chpaguri_D', 'ShivBari_D', 'PigonDPP_D', 'Samyaprm_D',
 'PreetDPP_D', 'Oilmilrd_D', 'MSRClgRd_D', 'ITICollg_L',
 'KatlaDPP_D', 'South_R_11', 'Shivangr_D', 'KnsgraRD_D',
 'PuranDPP_D', 'Domlur', 'AnprnDPP_D', 'Chndlrd_D',
'RmNyrDPP_D',
 'GMndiDPP_D', 'Kooriyad_D', 'Munduprm_D', 'ByePass_D',
 'SngihiRD_D', 'Sabalpur_D', 'Karnal', 'Shivalya_D',
'PnchmDPP_D',
 'Bahreya_I', 'JiswlDPP_D', 'Gobindgarh_DC', 'KarnalRd_D',
 'Bargawan_DC', 'Mughlpra_D', 'GutmgrCl_D', 'Perungudi_DPC',
 'BhemuDPP_D', 'Central_D_7', 'Patel_Nagar', 'SidculRd_D',
 'Kothuru_D', 'Wardno8_D', 'ThthiCwk_D', 'VidyaDPP_D',
'BaruaRd_D',
 'Babupaty_D', 'Bhankrot_DC', 'Trimulgherry_Dc', 'Surajpur_DC',
 'TrnptNgr_L', 'MissonRd_D', 'MJRDPP_D', 'AzmrddDPP_D',
'Jamalpur_D',
 'LNBRoad_D', 'Shop2DPP_D', 'DeVDPP_D', 'KSCLny_DC',
'GagiDPP_D',
 'HotelPrk_D', 'SnthiINGR_D', 'BypRDDPP_D', 'BhmrdDPP_D',
 'Vijayawada', 'Kidwai_D', 'Mharajpr_D', 'GrudwrRd_D',
'Adrshngr_D',
 'Krvnkuzy_D', 'PhdofDPP_D', 'CtyLgDPP_D', 'Pilani',
'StnRoad_DC',
 'Solaiprm_D', 'RailwyRd_D', 'Diakkawn_D', 'PiliKoti_D',
 'VislkNgr_DC', 'SaiTempl_D', 'NcsRd_DC', 'Arangadi_D',
 'LohiaDPP_D', 'PakridPP_D', 'BisnolDPP_D', 'PrmNrDPP_D',
 'BsnoiHPL_D', 'Gopa3PL_D', 'ShrprDPP_D', 'MnRDDPP_D',

'BllvMarg_D',
 'Farmnala_D', 'Katghara_D', 'KhandDPP_D', 'JngidDPP_D',
 'Tolichwk_L', 'Pringla_D', 'SurbhiTh_D', 'Greens_D',
'CivilStn_D',
 'Shivprasad_D', 'KirtiNgr_D', 'ModelTwn_P', 'Fairybnk_D',
 'Cnsrvila_D', 'BhunaDPP_D', 'Ukkadam_D', 'BChwkDPP_D',
'Jharia_DC',
 'Chrwpaty_D', 'CollgeRD_D', 'Pthrgoan_D', 'HelipadRD_D',
 'DltprDPP_D', 'Ranakant_D', 'Vandalur_Dc', 'Airport',
 'Rahatani_DPC', 'Bhrnikvu_D', 'HunthrVg_I', 'Awmpivng_D',
 'PmthuKlm_D', 'PanditRd_D', 'Chtrpuza_D', 'SantaNGR_D',
 'JalnaRd_D', 'Bazarrd_D', 'UmarDPP_D', 'CmtNgRod_D',
'KasyaDPP_D',
 'StteHW28_D', 'VijywdRD_D', 'Dehrird_D', 'Wardno7_D',
'NatunDPP_D',
 'Enayetpr_D', 'East_I_20', 'KtnRdDPP_D', 'Mapusa',
'Kothriya_DC',
 'Ymunpurm_D', 'TonkRoad_D', 'East_D_8', 'SmbjiCwk_D',
'Jabalpur',
 'Indrapri_DC', 'YashDPP_D', 'AchneraRD_D', 'DibngVly_D',
 'BnglorRd_D', 'PcrrdDPP_D', 'Murtinigr_D', 'Central_D_15',
 'JmpuCntr_D', 'Rajpura_D', 'Mulapali_D', 'LdnunDPP_D',
'PngnrRd_D',
 'Tejpal_M', 'RjghatRd_D', 'Pnchlght_D', 'KDRoad_D',
'farukngr_D',
 'SingCLNY_D', 'Jagrata_D', 'ThaneDPP_D', 'MdhsnDPP_D',
'Margao_Dc',
 'Nijgan_D', 'Rawatpur_D', 'Gurukrpa_D', 'JivanDPP_D',
 'AshokNagar_DC', 'BhmprDPP_D', 'KarjuDPP_D', 'Pothredy_D',
'_NAD',
 'ShbdnDPP_D', 'ClgRDDPP_D', 'Brpc', 'ShubsNGR_D', 'Beltnngdi_D',
 'Ldthlabh_D', 'KamalDPP_D', 'IndEstat_L', 'HnmntNgr_D',
 'ShivmDPP_D', 'BstndDPP_D', 'Cherukole_D', 'EmsPnmbi_D',
 'KaimgnjRD_D', 'Bhainpura_D', 'FatprDPP_D', 'RajRdDPP_D',
 'Mahad_D', 'MsjidDPP_D', 'PaikjNGR_D', 'BalibDPP_D',
'KcharaRD_D',
 'ChtwrDPP_D', 'MsmcyDPP_D', 'ElngoNgr_C', 'Rcocmplx_D',
 'PunjbiPd_D', 'Shanthi_D', 'Ponda_Dc', 'SirsaDPP_D', 'Mahim',
 'Paldi_D', 'SubrtDPP_D', 'Santalpr_D', 'TiloIDPP_D', 'Idgah_L',
 'KoralDPP_D', 'Nerul_D', 'Uppal_Dc', 'MhliaDPP_D',
'Bomsndra_L',
 'SukntDPP_D', 'Arsprmbu_D', 'MnimlaRd_D', 'UttarDPP_D',
 'ChatidPP_D', 'MdnprDPP_D', 'Kanakpur_D', 'East', 'MdothdRD_D',
 'CroadDPP_D', 'Sarjapur_D', 'SbhRDDPP_D', 'Central_D_4',
 'Thiruvlr_DC', 'Sangetha_D', 'NadthiCx_D', 'Naraynpr_D',
'Hathras',
 'AkkolRD_D', 'AnnaNGR_D', 'LamtiDPP_D', 'DiyoDPP_D',
'MunplDPP_D',
 'RoopNgr_D', 'RwStnDPP_D', 'BhrolDPP_D', 'Umargaon_DC',

```

    'Ramnagar_D', 'Majoor_D', 'BageDPP_D', 'MnbzrDPP_D',
'AkhraBzr_D',
    'MemariRD_D', 'ArickDPP_D', 'kalmpuza_D', 'BnkrGate_D',
'ColnyDPP_D', 'Muktsar_D', 'Patia', 'Rjndpara_D', 'BrezeDPP_D',
'GurpdDPP_D', 'Kothanur_L', 'Ricco_D', 'Palam', 'Prjapati_D',
'Gondkhry_H', 'South_D_20', 'Central_H_4', 'KalikDPP_D',
'Bareilly', 'STRdDPP_D', 'RatuaDPP_D', 'BazarDPP_D',
'lalaNGR_D',
    'GndhiChk_D', 'Mirapati_L', 'RhmgjDPP_D', 'Central_L_8',
'Kaura_D',
    'Khndyusn_D', 'AmbkaDPP_D', 'Nelmngla_L', 'IOTCEncl_L',
'AnadiDPP_D', 'JJCpxDPP_D', 'IdstrlAr_D', 'Mehsouri_D',
'HanumDPP_D', 'GovndNgr_DC', 'JthriDPP_DC', 'Karelibaug_DC',
'Bnsibtla_D', 'MjlprDPP_D', 'Sardhnrd_D', 'MbRoad_D',
'Central_D_10', 'Old', 'SliprDPP_DC', 'Kapleswr_D',
'Kdvantra_D',
    'SaduldPP_D', 'Pulgaon_DC', 'AkhirDPP_D', 'KrshnNgr_D',
'Parai_D',
    'Selaiyur_DC', 'Chinchwad_DC', 'NavdaCln_D', 'CBRoad_D',
'Sidrd_D',
    'ThanaDPP_D', 'Krusphrma_D', 'Mahuva_DC', 'Manchar_D',
'BargaDPP_D', 'NapitDPP_D', 'Rgstr0FC_D', 'Bhaluahi_D',
'Thikiri_D', 'RajpurRD_D'], dtype=object)

de['source_state'].unique()

array(['Uttar Pradesh', 'Madhya Pradesh', 'Karnataka', 'Haryana',
       'Maharashtra', 'Tamil Nadu', 'Gujarat', 'Delhi', 'Telangana',
       'Andhra Pradesh', 'Rajasthan', 'Assam', 'West Bengal',
       'Punjab',
       'Chandigarh', 'Goa', 'Uttarakhand', 'Jharkhand', 'Pondicherry',
       'Orissa', 'Himachal Pradesh', 'Kerala', 'Arunachal Pradesh',
       'Bihar', 'Meghalaya', 'Chhattisgarh', 'Jammu & Kashmir',
       'Dadra and Nagar Haveli', 'Mizoram', 'Tripura', 'Nagaland'],
      dtype=object)

de['source_state'].value_counts().to_frame().style.background_gradient
(cmap='Reds')

<pandas.io.formats.style.Styler at 0x20e66549110>

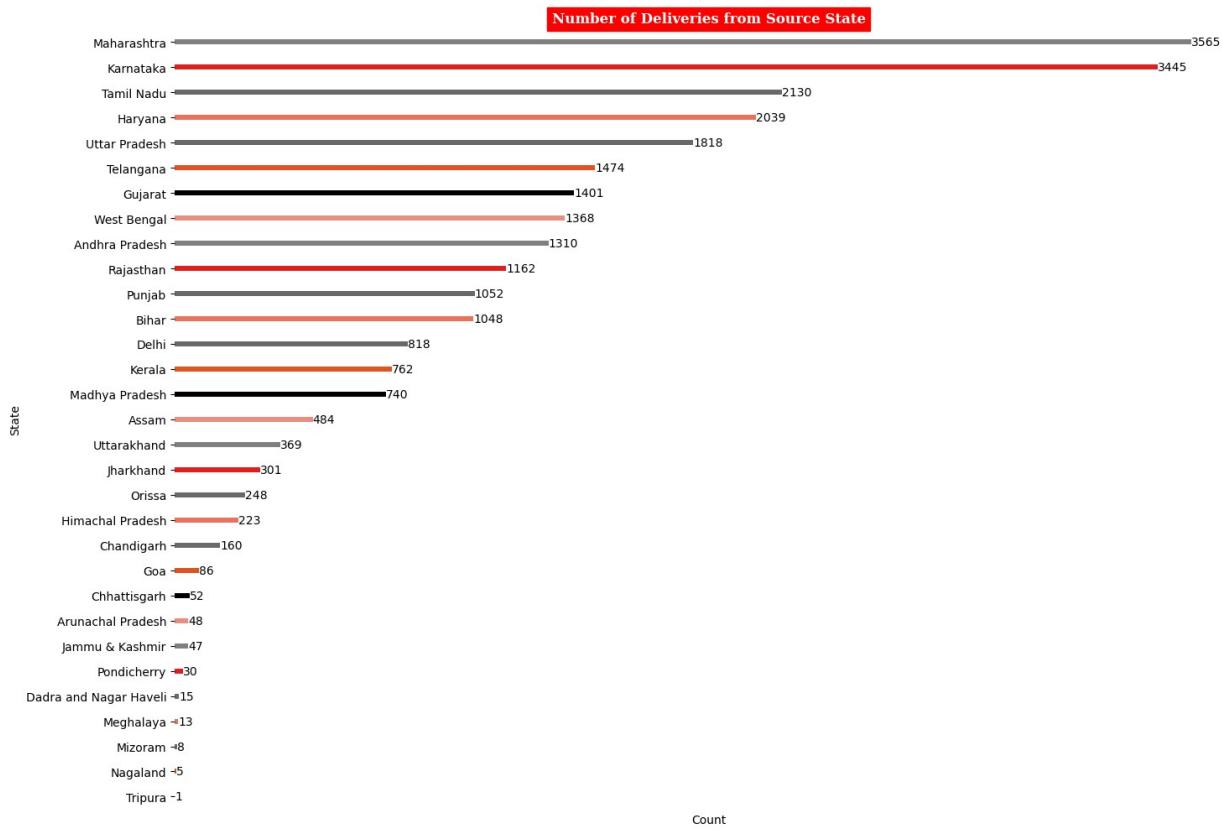
state_counts =
de['source_state'].value_counts().to_frame().reset_index()
state_counts.columns = ['State', 'Count']

plt.figure(figsize=(15,10))
a = sns.barplot(y='State', x='Count',
                 data=state_counts, palette=cp, width=0.2)
a.bar_label(a.containers[0], label_type='edge')
plt.xticks([])
```

```

plt.ylabel('State')
plt.xlabel('Count')
plt.title('Number of Deliveries from Source State', fontsize=12, fontfamily='serif', fontweight='bold', backgroundcolor='r', color='w')
plt.tight_layout()
sns.despine(bottom=True, left=True)
plt.show()

```



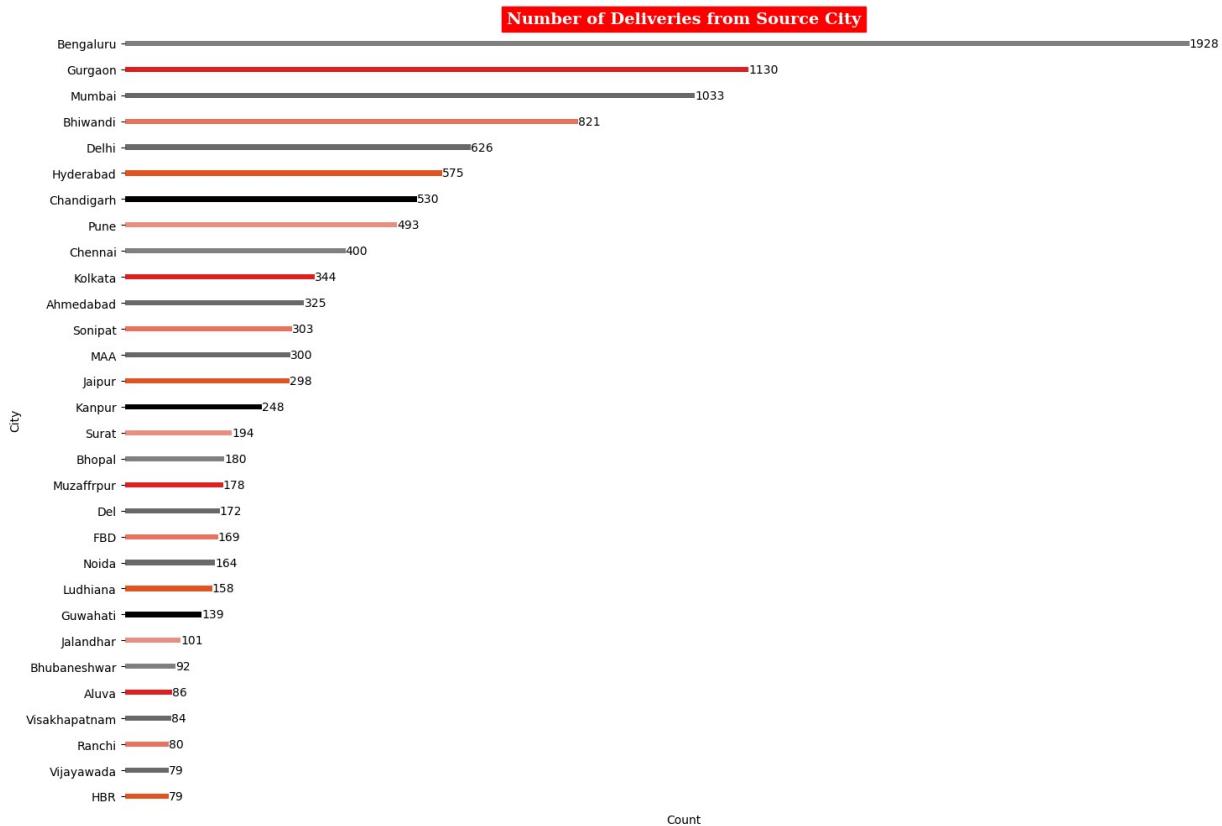
```

city_counts =
de['source_city'].value_counts().to_frame().reset_index()[:30]
city_counts.columns = ['City', 'Count']

plt.figure(figsize=(15,10))
a = sns.barplot(y='City', x='Count',
data=city_counts, palette=cp, width=0.2)
a.bar_label(a.containers[0], label_type='edge')
plt.xticks([])
plt.ylabel('City')
plt.xlabel('Count')
plt.title('Number of Deliveries from Source City', fontsize=14, fontfamily='serif', fontweight='bold', backgroundcolor='r', color='w')
plt.tight_layout()

```

```
sns.despine(bottom=True, left=True)
plt.show()
```



Insights:

Source State contributors

- **Maharashtra, Karnataka, Tamil Nadu, Haryana, and Uttar Pradesh** are the top contributors where maximum bookings are recorded in this month indicating significant engagement.

Source City contributors

- Cities like **Bengaluru, Gurgaon, Mumbai, Bhiwandi, Delhi, Hyderabad** where the major no.of booking are recorded.

```
de.describe().T
```

	count	mean
\		
trip_creation_time	26222	2018-09-22 13:58:56.740969728
od_start_time	26222	2018-09-22 17:49:54.012840448
od_end_time	26222	2018-09-22 22:49:00.449498112
start_scan_to_end_scan	26222.0	298.553375

actual_distance_to_destination	26222.0	92.533051
actual_time	26222.0	200.92659
osrm_time	26222.0	90.785332
osrm_distance	26222.0	114.975334
segment_actual_time	26222.0	199.095642
segment_osrm_time	26222.0	101.793343
segment_osrm_distance	26222.0	125.587128
segment_actual_time_sum	26222.0	199.095642
segment_osrm_time_sum	26222.0	101.793343
segment_osrm_distance_sum	26222.0	125.587128
od_total_time	26222	0 days 04:59:06.436657725
od_time_diff_hour	26222.0	4.985121

		min \
trip_creation_time	2018-09-12 00:00:16.535741	
od_start_time	2018-09-12 00:00:16.535741	
od_end_time	2018-09-12 00:50:10.814399	
start_scan_to_end_scan	20.0	
actual_distance_to_destination	9.001351	
actual_time	9.0	
osrm_time	6.0	
osrm_distance	9.0729	
segment_actual_time	9.0	
segment_osrm_time	6.0	
segment_osrm_distance	9.0729	
segment_actual_time_sum	9.0	
segment_osrm_time_sum	6.0	
segment_osrm_distance_sum	9.0729	
od_total_time	0 days 00:20:42.168787	
od_time_diff_hour	0.345047	

		25% \
trip_creation_time	2018-09-17 03:57:50.900417024	
od_start_time	2018-09-17 07:43:36.525784320	
od_end_time	2018-09-17 15:10:35.615369472	
start_scan_to_end_scan	90.0	
actual_distance_to_destination	21.65415	
actual_time	51.0	

osrm_time	25.0
osrm_distance	27.71915
segment_actual_time	50.0
segment_osrm_time	25.0
segment_osrm_distance	28.429099
segment_actual_time_sum	50.0
segment_osrm_time_sum	25.0
segment_osrm_distance_sum	28.429099
od_total_time	0 days 01:30:58.665517750
od_time_diff_hour	1.516296

trip_creation_time	2018-09-22 03:33:30.255023104
od_start_time	2018-09-22 07:17:15.379571712
od_end_time	2018-09-22 14:46:05.410478848
start_scan_to_end_scan	152.0
actual_distance_to_destination	35.044329
actual_time	84.0
osrm_time	39.0
osrm_distance	43.54355
segment_actual_time	83.0
segment_osrm_time	42.0
segment_osrm_distance	45.797649
segment_actual_time_sum	83.0
segment_osrm_time_sum	42.0
segment_osrm_distance_sum	45.797649
od_total_time	0 days 02:32:20.203949500
od_time_diff_hour	2.538946

trip_creation_time	2018-09-27 19:55:17.273207040
od_start_time	2018-09-27 23:22:20.105725952
od_end_time	2018-09-28 03:19:50.211971840
start_scan_to_end_scan	307.0
actual_distance_to_destination	65.557392
actual_time	167.0
osrm_time	72.0
osrm_distance	85.443949
segment_actual_time	166.0
segment_osrm_time	79.0
segment_osrm_distance	91.023573
segment_actual_time_sum	166.0
segment_osrm_time_sum	79.0
segment_osrm_distance_sum	91.023573
od_total_time	0 days 05:07:17.158769
od_time_diff_hour	5.121433

trip_creation_time	2018-10-03 23:59:42.701692
od_start_time	2018-10-06 04:27:23.392375

```

od_end_time           2018-10-08 03:00:24.353479
start_scan_to_end_scan          7898.0
actual_distance_to_destination      1927.447754
actual_time                  4532.0
osrm_time                     1686.0
osrm_distance                 2326.199219
segment_actual_time            4504.0
segment_osrm_time              1938.0
segment_osrm_distance          2640.924805
segment_actual_time_sum        4504.0
segment_osrm_time_sum          1938.0
segment_osrm_distance_sum      2640.924805
od_total_time                5 days 11:38:33.117274
od_time_diff_hour             131.642533

```

	std
trip_creation_time	NaN
od_start_time	NaN
od_end_time	NaN
start_scan_to_end_scan	441.116974
actual_distance_to_destination	209.952652
actual_time	385.728271
osrm_time	185.558731
osrm_distance	254.426529
segment_actual_time	382.145752
segment_osrm_time	216.205933
segment_osrm_distance	286.6698
segment_actual_time_sum	382.145752
segment_osrm_time_sum	216.205933
segment_osrm_distance_sum	286.6698
od_total_time	0 days 07:21:14.957234047
od_time_diff_hour	7.354155

```
de.describe(include='object').T
```

	count	unique	\
segment_key	26222	26222	
trip_uuid	26222	14787	
source_name	26222	1496	
destination_name	26222	1466	
source_city	26222	1239	
source_place	26222	1246	
source_state	26222	31	
destination_city	26222	1236	
destination_place	26222	1217	
destination_state	26222	32	

	top
freq	
segment_key	trip-153671041653548748+IND209304AAA+IND000000ACB

```

1                                         trip-153717306559016761
trip_uuid
8                                         Gurgaon_Bilaspur_HB (Haryana)
source_name
1052                                         Gurgaon_Bilaspur_HB (Haryana)
destination_name
928                                         Bengaluru
source_city
1928                                         Bilaspur_HB
source_place
1052                                         Maharashtra
source_state
3565                                         Bengaluru
destination_city
1863                                         Bilaspur_HB
destination_place
928                                         Karnataka
destination_state
3497

de['destination_city'].unique()

array(['Gurgaon', 'Kanpur', 'Chikblapur', 'Doddablpur', 'Chandigarh',
       'Mumbai', 'Hospet', 'Bellary', 'Sandur', 'Chennai',
       'Bengaluru',
       'HBR', 'Surat', 'Delhi', 'PNQ', 'Faridabad', 'Kolhapur',
       'Shirala',
       'Ratnagiri', 'Anantapur', 'Hyderabad', 'Sindagi', 'Gulbarga',
       'Indi', 'Aland', 'Jaipur', 'Satna', 'Janakpuri', 'Guwahati',
       'Unnao', 'Gadarwara', 'Bareli', 'Shirdi', 'Sinnar',
       'Sangamner',
       'Shrirampur', 'Kopargaon', 'Vaijiapur', 'Nashik', 'Kolkata',
       'Hoogly', 'Hooghly', 'Pavagada', 'Puttaprthi', 'Sivasagar',
       'Medchal', 'Odnchtram', 'Batlagundu', 'Vadipatti',
       'Kodaikanal',
       'Palani', 'Nakodar', 'Kapurthala', 'Jalandhar', 'Yavatmal',
       'Atapadi', 'Sangola', 'Bhandara', 'Savner', 'Kurnool',
       'Palwal',
       'FBD', 'TalwandiSabo', 'Mansa', 'Jhunir', 'Bhatinda',
       'Bhiwandi',
       'Barnala', 'Murbad', 'AnandprShb', 'RoopNagar', 'Puttur',
       'Kadaba',
       'Chittapur', 'Sedam', 'Chincholi', 'Naraingarh', 'Ludhiana',
       'Ahmedabad', 'Kadi', 'Dola', 'Jabalpur', 'MAA', 'Parli',
       'Ambajogai', 'Pune', 'Loha', 'Gangakher', 'Barjora',
       'Bishnupur',
       'Bankura', 'Silvassa', 'Junagadh', 'Bhanvad', 'Porbandar',
       'Dhoraji', 'Upleta', 'Jetpur', 'Choutuppall', 'Suryapet',
       'Vijayawada', 'Nalgonda', 'Miryalguda', 'Khammam', 'Vadnagar',
       'Palanpur', 'Deesa', 'Mehsana', 'Katni', 'Kodinar', 'Talala'],

```

'Una', 'Chamarjngr', 'Mysore', 'Kollegala', 'Tirumakudalu',
'Malavalli', 'Krishnarajngr', 'Gonikoppal', 'HDKote', 'Unjha',
'Bhabhar', 'Radhanpur', 'Rajamundry', 'Visakhapatnam',
'Sawantwadi', 'Kankavali', 'Bhopal', 'Bhubaneshwar',
'Allahabad',
 'Moradabad', 'Rudrapur', 'Sonipat', 'Modasa', 'Khedbrahma',
 'Himmatnagar', 'Sasaram', 'Ranchi', 'Cuddalore', 'Chidambaram',
 'Sirkazhi', 'Karaikal', 'Nagapattinm', 'Pondicherry',
'Thiruvarur',
 'GZB', 'Khambhat', 'Anand', 'Degloor', 'Udgir', 'Latur',
'Nanded',
 'Noida', 'Umreth', 'Nadiad', 'Panruti', 'Pennadam',
'Chinnasalem',
 'Villupuram', 'Neyveli', 'Virudhchlm', 'Jhalda', 'Purulia',
'Hura',
 'Durgapur', 'Bhadrak', 'Goa', 'Balurghat', 'Meham', 'Hisar',
 'Ambur', 'Tiruppattur', 'Haridwar', 'Kotdwara', 'Narsapur',
 'Kamareddy', 'Bodhan', 'Medak', 'Banswada', 'Yellareddy',
 'Dhrangadhra', 'Halvad', 'Gangavathi', 'Koppal', 'Jahu',
 'BilaspurHP', 'JognderNgr', 'Kharagpur', 'Jhargram',
 'ChandroknaRD', 'Kirauli', 'BLR', 'Lakhimpur', 'Sitapur',
'Gola',
 'Dhaurahara', 'Mangalore', 'Canacona', 'Vansda',
'Mananthavady',
 'Lucknow', 'Silchar', 'Nakhatrana', 'Bhuj', 'Pundibari',
 'LowerParel', 'Changlang', 'Dahanu', 'Boisar', 'Chodavaram',
 'Bhalukpong', 'Tezpur', 'Rajampet', 'Tirupati', 'Koduru',
'GGN',
 'Sriklahsti', 'Venktagiri', 'Gudur', 'Roha', 'Mahad', 'Pen',
'CCU',
 'Amdavad', 'AMD', 'Gosainganj', 'Akbarpur', 'Muzaffrpur',
'Purnia',
 'Aurangabad', 'KN', 'Phagwara', 'Pandhurna', 'Betul', 'Sausar',
 'Tamluk', 'Panskura', 'Haldia', 'Madurai', 'Dindigul',
'Namakkal',
 'Erode', 'Aligarh', 'Mainpuri', 'Shikohabad', 'Firozabad',
'Rajam',
 'Salur', 'Srikakulam', 'Palakonda', 'Parvathipuram',
'Narasnpeta',
 'Palasa', 'Paralakhemundi', 'Tekkali', 'Nalasopara', 'Hajo',
'NOI',
 'Dalhousie', 'Chamba', 'Pathankot', 'Baharampur', 'Dhulian',
 'Malda', 'Malvan', 'Hoskote', 'Shujalpur', 'Shajapur',
'Ambabadi',
 'OK', 'Amritsar', 'Coimbatore', 'Jasai', 'Tirchngode',
'Mettur',
 'Kurseong', 'Darjeeling', 'Tiruchi', 'Dadri', 'Del', 'Rangia',
 'Nalbari', 'Bilasipara', 'Lakhipur', 'Dhubri', 'Vellore',
'Ajmer',

'Pali', 'Jodhpur', 'Gotan', 'Gajraula', 'Rampur', 'Amroha',
'Dholpur', 'Lalitpur', 'Gwalior', 'Datia', 'Thirthurpondi',
'Pushpavanam', 'Dhanbad', 'Ashokngr', 'Guna', 'Burhanpur',
'Hassan', 'Margherita', 'SrinagarUK', 'Chamoli', 'Gohpur',
'Itanagar', 'Silapathar', 'Pasighat', 'Mirzapur', 'Ghazipur',
'Dharwad', 'Gokak', 'Hubli', 'Ramdurg', 'Gadag', 'Rona',
'Bagalkot', 'Renukoot', 'Anpara', 'Singrauli', 'Robertsganj',
'Panipat', 'Berhampur', 'Ranebennur', 'Haveri', 'Alwar',
'Bhilwara', 'Udaipur', 'Gandhidham', 'Solapur', 'Belgaum',
'Muktsar', 'Moga', 'Jagatsghpr', 'Paradip', 'Kendrpara',
'Osmanabad', 'Barshi', 'Addanki', 'Kanigiri', 'Kandukur',
'Ongole',
'Bokaro', 'Sirsi', 'Sagara', 'Muzaffrngr', 'Dehradun',
'Deoband',
'Chhatarpur', 'Siwan', 'Nawada', 'Chandi', 'BiharSarif',
'Rajgir',
'Pallakad', 'Vadakkencherry', 'Thrissur', 'Kanakapura',
'Chanapatna', 'Mandy', 'Roorkee', 'Rishikesh', 'Manjeshwar',
'Surathkal', 'Jamshedpur', 'Vadodara', 'Sheikhpura',
'Bakhtiarpur',
'Godhra', 'Dahod', 'Tirupur', 'Kendujhar', 'Barbil',
'Karanjia',
'Rewari', 'Dharuhera', 'Neemrana', 'Hanumangarh', 'Sirsa',
'Ganga',
'Arrah', 'Arwal', 'Jhajjar', 'Bhiwani', 'Kabuganj', 'Kolasib',
'Bardhaman', 'Asansol', 'Rupnarayanpur', 'Midnapore', 'Jalna',
'Sillod', 'Nellore', 'Chapra', 'Nakashipara', 'Plassey',
'SultnBthry', 'Rawatsar', 'Kurukshtetra', 'Assandh', 'Pehowa',
'Kaithal', 'Nuzvid', 'Kaikaluru', 'Gudivada', 'Machilipatnam',
'Nowda', 'Domkal', 'Nazirpur', 'Kadthal', 'Haliya',
'Devarakonda',
'Kalwakurthy', 'Khargram', 'Rampurhat', 'Morgram',
'Ghanashyampur',
'Kandi', 'Ragunthgnj', 'Lalgola', 'Sagardighi', 'Jangipur',
'AhmedNagar', 'Ashti', 'Parner', 'Bilaspur', 'Baheri',
'Puranpur',
'Hailakandi', 'Karimganj', 'Jorhat', 'SundarNgr', 'Kullu',
'Mandi',
'Hiriyur', 'Davangere', 'Chitradurga', 'Draksharamam',
'Madhubani',
'Jaynagar', 'Baddi', 'Solan', 'Parwanoo', 'Shegaon', 'Mehkar',
'Akola', 'Chiplun', 'Karad', 'Khed', 'Islampur', 'Raichur',
'Wanaparthi', 'JoguGadwal', 'Modinagar', 'Meerut', 'Saharsa',
'Triveniganj', 'Supaul', 'Madhepura', 'Araria', 'Raniganj',
'Simrahi', 'Sheohar', 'Pupri', 'Sitamari', 'Srisailam',
'Nandyal',
'Bgnnpalle', 'Tiptur', 'Mallapur', 'Dandeli', 'Athani',
'Bijapur',
'Jind', 'Gohana', 'Rohtak', 'Patiala', 'Beawar', 'Bijainagar',

'Darbhanga', 'Benipur', 'Jhanjharpur', 'Krishnarajpet',
'Channaraya', 'Khagaria', 'Naugchia', 'Katihar', 'Ratia',
'Dharmavram', 'Kadiri', 'Rayachoti', 'Pulivendula',
'YamunaNagar',
'PaontSahib', 'Kishangarh', 'Parbatsar', 'Merta', 'Degana',
'Makrana', 'Raigarh', 'Ranikhet', 'Nainital', 'Pithorgarh',
'Almora', 'Godda', 'Bharatpur', 'Bayana', 'Deoria', 'Salempur',
'Gorakhpur', 'Kaptanganj', 'Kushinagar', 'Bettiah',
'Narktiganj',
'Dhaka', 'Mungeli', 'Kawardha', 'Pakur', 'Dumka', 'Bangana',
'Bhota', 'Nadaun', 'Bahadurgarh', 'Thakurdwara', 'Najibabad',
'Kanth', 'Dhampur', 'Khanpur', 'Mahbubabad', 'Warangal',
'Chandausi', 'Aonla', 'Sambhal', 'Ratlam', 'Kolaghat',
'Bagnan',
'Lalru', 'Kashipur', 'Ramnagar', 'Sikandarpur', 'Ratanpura',
'Sahatwar', 'Balaghpat', 'Motihari', 'Raxaul', 'Zahirabad',
'Humnabad', 'Bidar', 'Narayankhed', 'Gooty', 'Guntakal',
'Rayadurgam', 'Kalyandurg', 'Gandhinagar', 'Amd', 'Patran',
'Samana', 'Manuguru', 'Sathupally', 'Shamli', 'Bassi', 'Dausa',
'Hindaun', 'Lalsot', 'Karauli', 'Gangapur', 'Nawalgarh',
'Pilani',
'Khamphalia', 'Bhatiya', 'Dwarka', 'Kakdwip', 'Ambah',
'Kilimanoor', 'Kalluvathukal', 'Attingal', 'Limbdi', 'Botad',
'Surendranagar', 'Dudu', 'Phulera', 'Renwal', 'Dumraon',
'Jagdishpur', 'Buxar', 'DalsinghSarai', 'Rusera', 'Manjhaul',
'Sikandrabd', 'Jewar', 'Pahasu', 'Anupshahar', 'Neyatinkra',
'Kallikkad', 'Etawah', 'Auraiya', 'Kahalgaon', 'Bhagalpur',
'Panaji', 'Jagraon', 'Raikot', 'Pilkhuwa', 'Hapur', 'Dholi',
'Samastipur', 'Nawanshahr', 'Kaman', 'Karimnagar', 'Metpally',
'Jagtial', 'DhrmpuriTS', 'Mancherial', 'Tiruvalla', 'Haripad',
'Mundakayam', 'Khurdha', 'Khanna', 'Rajpura', 'Adoor',
'Kottarakkara', 'Pthnmthitt', 'Punalur', 'Kollam', 'Shirpur',
'Dhule', 'Nandurbar', 'Sakri', 'Shahada', 'AurngbadBR',
'Kanti',
'Gadchiroli', 'Chamorshi', 'Pandharpur', 'Zirakpur', 'Aluva',
'Chalisgaon', 'Kannad', 'Deoli', 'Bhadaur', 'Hindupur',
'Hamirpur',
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'Banda',
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 'MPward_D', 'SourvDPP_D', 'Varachha_DC', 'SaiBansi_D',
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 'YeolaRD_D', 'TgrniaRD_I', 'North_I_4', 'Bandel_D', 'DC',
 'PnukndRD_D', 'Gokulam_D', 'Babupaty_D', 'Bomsndra_HB',
 'MROoffce_D', 'Alwal_I', 'Palani_D', 'RT0ofice_D', 'lalaNGR_D',
 'Athithnr_DC', 'RjnndraRd_D', 'ChowkDPP_D', 'DPC', 'Mohali',
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 'BnsllNgr_D', 'Tathawde_H', 'SivjiCWK_D', 'Busstand_D',
 'Central_DPP_1', 'StnRdDPP_D', 'BhowmDPP_D', 'Samrvrni_D',
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'Bhaleti_D',
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'Dayanand_D',
'NaginaRD_D', 'Nrsampt_D', 'Yellanda_D', 'HunterRd_I',
'Ganesh_D',
'KdidmCLY_D', 'Khwssrai_D', 'Khjurwli_DC', 'Harop_D',
'OnkarDPP_D',
'BajprDPP_D', 'Vaishali_D', 'BhwniGnj_D', 'MubarDPP_D',
'PnchmDPP_D', 'Kosmi_D', 'RajaBzr_D', 'Kairiyat_D', 'Mohim_D',
'EBroad_D', 'Bidar', 'Datatrya_D', 'StatonRd_D', 'Verpatem_D',
'RailGate_D', 'Shankrpa_D', 'Kalol_DC', 'Chandkheda_Dc',
'MheshNGR_D', 'PODPP_D', 'AskNagar_D', 'KarnalRd_D',
'DmodrNGR_D',
'IndraCln_D', 'MndwrRod_D', 'NWclyDPP_D', 'HnsChowk_D',
'Ward6DPP_D', 'NavldiDPP_D', 'Pilani', 'JdswarRD_D',
'Kalyanpr_D',
'StnRoad_DC', 'KlngrDPP_D', 'MrenTirh_D', 'Tejpal_I',
'Krvnkuzy_D',
'Pariplly_D', 'NrainaRD_D', 'NarenaRD_D', 'ChomuRD_D',
'Nishangr_D', 'Wardno13_D', 'Sarswati_D', 'Wardno4_D',
'Purbari_D',
'GTRoad_D', 'SJRoad_D', 'Kanongyn_D', 'DcntCLY_D',
'Arlumodu_D',
'Mutvila_D', 'MhraChng_D', 'AryaNagr_D', 'Kharghar_D',
'NdiaTola_D', 'Pbroad_DC', 'ZuariNgr_IP', 'Goa', 'HapurRD_D',
'Swargash_D', 'WardNo4_D', 'Haripur_D', 'KamnHbRD_I',
'GunjRDPP_D',
'Aravind_D', 'HanumDPP_D', 'Hitech_D', 'TKRoad_D',
'Kumrpurm_D',
'MunplDPP_D', 'Gobindgarh_DC', 'Town_D', 'Amankovl_D',
'Klskrpt_D', 'PostofJN_D', 'KrantiNgr_D', 'MIDCAvdn_I',
'DhuleRd_D', 'DhuleRoad_D', 'Nandrbars_D', 'Mahindra_D',
'Khar West_Dc', 'RajCmplx_D', 'Balaji Nagar', 'Peedika_H',
'BhadgDPP_D', 'KolheDPP_D', 'BChwkDPP_D', 'Parigi_D',
'KanpurRd_D',
'StatinRD_D', 'Rawatpur_D', 'JilRDDPP_D', 'Kotwali_D',
'Mlkpura_D',
'GayatriN_D', 'Arulimod_D', 'Ajnari_D', 'NehruNGR_D',
'Court_D',
'GovndNgr_DC', 'barkarRd_D', 'Bokule_H', 'JyotiNgr_D',
'BrlwgDPP_D', 'Chikdply_I', 'Naraynpr_D', 'ModelTwn_P',
'Ward19_D',

'SttinDPP_D', 'PalikDPP_D', 'Padra_D', 'WebelDPP_D',
'Itachnnda_D',
 'Pshimptra_D', 'Psthrjhr_D', 'B0B_D', 'Truptingr_D', 'Virar_DC',
 'Skynet_INT', 'Shop3DPP_D', 'Vepmpttu_DC', 'IndEstat_I',
 'Paschim_DC', 'LB-Nagar_Dc', 'CotnGren_M', 'MiraRoad_M',
 'ShivBari_D', 'Vadodara', 'ArkonmRD_D', 'Central_DPP_4',
 'Chakan_D', 'Mdiclcly_D', 'ColageRD_D', 'Umalodge_D',
'SriDPP_D',
 'WardNo3_D', 'Shillong', 'NamoNagr_D', 'ShsmlDPP_D',
'FatehpRd_I',
 'PBRDDPP_D', 'KotwaliN_D', 'MduraiRD_D', 'Kacheri_D',
'KhandDPP_D',
 'Jamalpur_D', 'BgwriDPP_D', 'SmClyDPP_D', 'Madarpur_D',
 'Nirjanpur_L', 'PonaniRD_D', 'ManhrBld_D', 'DumDum_DPC',
 'KaaduRd_D', 'Blmrgnst_D', 'KrthiKyn_D', 'StationRD_D',
'Satara_D',
 'BstndDPP_D', 'KmkshBul_D', 'Prbhtngr_D', 'Kakrmath_D',
 'Beltnrgdi_D', 'MarketRd_D', 'Veersagr_I', 'Pazhvedu_D',
 'Pshrikvu_D', 'ZamQuatr_D', 'Mandodi_D', 'IdstrlAr_D',
 'Thiruviz_D', 'Vadasari_D', 'Poondi_D', 'VaiklsRT_D',
'MukkuRD_D',
 'Fairybnk_D', 'kalmpuza_D', 'nagar_D', 'Badeplly_D', 'SH71_D',
 'Sbrmnprm_D', 'HsptlRod_D', 'Mrthndpr_D', 'Puduvalvu_D',
 'Konapara_D', 'CmtNgRod_D', 'Annangr_D', 'goplpurm_D',
 'Mthrapuri_D', 'Kmrnjngr_D', 'Chithbrm_D', 'PriyrNGR_D',
 'Pinjore_DC', 'AmtlaDPP_D', 'JhumanCk_D', 'Msstreet_DC',
 'Krsnakcl_D', 'Kovil_D', 'AshkTalk_D', 'Ward25_D', 'TherSRT_D',
 'Ukkadam_D', 'RtlamNka_D', 'Sahni_D', 'Palikval_D',
'Ward7DPP_D',
 'Srvdyckw_D', 'VijywdRD_D', 'BhogdDPP_D', 'MuthpTmp_D',
'BMRd_D',
 'Shanthi_D', 'Vijdurg_D', 'Ambedkar_D', 'Sunku_D', 'KolarRd_D',
 'FshryOFC_D', 'Artclgrd_D', 'Venkatsa_DC', 'Tuminkte_D',
 'PlsrdDPP_D', 'ViksClny_D', 'Barout_D', 'Wardno10_D',
'Thvrlrsrt_D',
 'Palladam_DC', 'Techrcly_D', 'Wardno7_D', 'Brplcwk_D',
 'GangDPP_D', 'Banshkri_DC', 'HousngBd_D', 'NH117_D',
'Arsprmbu_D',
 'Chnglptu_DC', 'Achipkam_D', 'Sudimala_D', 'Perkadrd_D',
 'Radhaprm_D', 'AsrplmRd_DC', 'VdkkuSrt_I', 'MrktYrd_DC',
 'Rajula_DC', 'SriVnktpm_D', 'UdnkdiRD_D', 'Shnmgrpm_D',
 'VidyaNgr_D', 'SKRoad_D', 'Uppal_L', 'BaraLoha_D',
'Barmasia_D',
 'D', 'AmbedDPP_D', 'LaxmiNGR_D', 'Kataram_D', 'JwahrNGR_D',
 'Srirampt_D', 'BnglorRd_D', 'Greenmkt_D', 'KndlDPP_D',
 'Pdmavati_D', 'JydevNGR_D', 'Civlline_D', 'ChngiDPP_D',
 'RjnldrNgr_DC', 'PiliKoti_D', 'Gurukrpa_D', 'TBCross_D',
 'CollgeRD_D', 'North', 'GwhRDDPP_D', 'Thiruvlr_DC',
'TmpleSrt_D',

'Vllyaprm_D', 'RamnadRD_D', 'ThrbadRD_D', 'Rawlgaon_D',
'Malegaon_D', 'South_D_12', 'Central_D_7', 'Wrd12DPP_D',
'Shahapur_D', 'HBColny_D', 'Ponda_Dc', 'RajpurRD_D',
'NorprRD_D',
 'ThanuDPP_D', 'Salem', 'PC', 'EraguDPP_D', 'Antop_Hill',
 'AadiDPP_D', 'TrnptNgr_L', 'Trimulgerry_Dc', 'Panvel_D',
 'Mangalam_D', 'ShantiNg_D', 'Viveka_DC', 'MJRDPP_D',
'Samarth_D',
 'BaliaMod_D', 'MhliaDPP_D', 'Ganeshwr_D', 'KatlaDPP_D',
 'Trmltmpl_D', 'kankroli_D', 'Mehmdpur_P', 'Hanmkond_D',
 'RadhaCpx_D', 'MndiRoad_D', 'Mohnprwa_D', 'Ward11_D',
'Mnanthla_H',
 'ShjnprRD_D', 'Eaglvari_D', 'PhdofDPP_D', 'Kelasahi_D',
 'Kdthdstt_D', 'TnhbBlkC_D', 'VagaiNgr_D', 'LxmntDPP_D',
 'BhmrDPP_D', 'Ameenpur_I', 'KdrShrRd_D', 'AlathurRD_D',
 'Thsil3PL_D', 'KKndrDPP_D', 'BhunaDPP_D', 'LFRoad_D',
'RgvdrDPP_D',
 'MandyaRD_D', 'Mlydpthr_D', 'Davisdle_D', 'HajiprRD_D',
 'MnBzrDPP_D', 'Talaiya_D', 'NharuExt_D', 'NngrgnRd_D',
 'SrnprHwy_D', 'Margao_Dc', 'Tejpal_M', 'Valluvar_D',
'RLSTNDPP_D',
 'War5DPP_D', 'Dilliyan_D', 'BhrolDPP_D', 'NaginaRd_D',
 'Sitarmrd_D', 'Kadugodi_D', 'Mahuva_DC', 'Shahdara',
'KakaCplx_D',
 'ConduDPP_D', 'Pothredy_D', 'APMCYard_D', 'VasaviNg_D',
'Kalyan',
 'Barwala', 'Central_D_5', 'PaikjNGR_D', 'Chaitnya_D',
'AsnsdhRD_D',
 'GndhiNgr_D', 'KhdimDPP_D', 'RPRoad_D', 'Swamylyt_D',
'Kidwai_D',
 'NagpurRd_D', 'DelRdDPP_D', 'ColegRd_D', 'Shekhpur_D',
 'MngaldPP_D', 'PrmNrDPP_D', 'BhwanDPP_D', 'MohnVRTL_D',
 'MohanNgr_C', 'PigonDPP_D', 'Chpaguri_D', 'Manikndm_H',
 'Palakrty_D', 'PreetDPP_D', 'Kothapet_D', 'ChtrGIDC_IP',
'Delhi',
 'ITICollg_L', 'KisanCo_D', 'LdnunDPP_D', 'Mhdiptnm_C',
 'Shivangr_D', 'KnsgraRD_D', 'Udupi', 'Sector02_C',
'Bomsndra_PC',
 'Vijayawada', 'Chndlpld_D', 'AkkolRD_D', 'MnbzrDPP_D',
 'Munduprm_D', 'EmsPnmbi_D', 'BSarani_D', 'Bareilly',
'WardNo1_D',
 'SadarHPL_D', 'Karnal', 'BgnprDPP_D', 'Mughlpra_D',
'SainkSCL_D',
 'Sohagpur_D', 'Sholiganallur_Dc', 'MdhsnDPP_D', 'Kadipur',
 'Kothuru_D', 'Wardno8_D', 'BaruaRd_D', 'Potheri', 'ChrlidPP_D',
 'Chatrpr_DC', 'MBTRd_DC', 'Sadras_D', 'AzmrDPP_D',
'LNBroad_D',
 'Shop2DPP_D', 'DeVDPP_D', 'GagiDPP_D', 'BodomBzr_DC',
'HotelPrk_D',

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'Mainrd_D', 'Pandriba_L', 'SnthiNGR_D', 'CroslySRT_D',
'BypRDDPP_D', 'JrjoldPP_D', 'UmarDPP_D', 'Mharajpr_D',
'Cnsrvila_D', 'Gurkhari_D', 'East_L_23', 'JthriDPP_DC',
'CtyLgDPP_D', 'SadulDPP_D', 'PedakRd_P', 'RailwyRd_D',
'Solaiprm_D', 'Bhabua_D', 'Chukhndi_D', 'Todapur_DC',
'VislkNgr_DC', 'SaiTempl_D', 'NcsRd_DC', 'Nullipad_D',
'NapitDPP_D', 'MrdiVlge_D', 'LohiaDPP_D', 'PakriDPP_D',
'BisnolDPP_D', 'Gopa3PL_D', 'Nehru3PL_D', 'MnRDDPP_D',
'Bahreya_I',
'ThthiCwk_D', 'HSR_Layout_PC', 'Sraccmplx_D', 'Katghara_D',
'Mhimapur_D', 'Nimachrd_D', 'Kdvantra_D', 'Chtrpuzza_D',
'Veluthur_D', 'Greens_D', 'SurbhiTh_D', 'Shivprsad_D',
'BawliDPPP_D', 'Rathnam_D', 'HesglDPP_D', 'TonkRoad_D',
'MSRClgRd_D', 'Shivalya_D', 'JatniDPP_D', 'Mangol_DC',
'Pthrgoan_D', 'Chrwpaty_D', 'HelipadRD_D', 'Farmnala_D',
'ShbdnDPP_D', 'Ranakant_D', 'Chmpmura_I', 'North_D_3',
'ShubsNGR_D', 'Mrtrklgr_D', 'AwmpiVng_D', 'HunthrVg_I',
'Feroke_H',
'Pringla_D', 'SantaNGR_D', 'Bazarrd_D', 'JalnaRd_D',
'GhtimDPP_D',
'IndraNgr_D', 'RmNyrDPP_D', 'HsnRdDPP_D', 'Puthalam_D',
'Agraharm_DC', 'Dehrird_D', 'BasthDPP_D', 'SubrtDPP_D',
'FatprDPP_D', 'Nijgan_D', 'East_I_20', 'KtnRdDPP_D', 'Mapusa',
'Pnjbiyon_D', 'Patel Nagar', 'East_D_8', 'Rjndrngr_D', 'Old
City',
'YashDPP_D', 'Aliganj', 'Agra', 'Nerul_D', 'Murtingr_D',
'PcrrdDPP_D', 'BsStdDPP_D', 'SashPhkn_D', 'KalikDPP_D',
'Lakshmi_D', 'Whitefld_L', 'Lngrguda_D', 'DMComDPP_D',
'Pnchlght_D', 'KDRoad_D', 'NavdaCln_D', 'KaimgnjRD_D',
'farukngr_D', 'CroadDPP_D', 'RatuaDPP_D', 'JivanDPP_D',
'BhmprDPP_D', 'Vishakhapatnam', 'GoalpDPP_D', 'MlnprDPP_D',
'TiloIDPP_D', 'Wardnor4_D', 'Ldthlabh_D', 'MahmurGj_IP',
'KamalDPP_D', 'PuranDPP_D', 'Cherukole_D', 'Bhaipura_D',
'MnimlaRd_D', 'KeRoad_D', 'MsjidDPP_D', 'KarjuDPP_D',
'VidyaDPP_D',
'KoralDPP_D', 'Majoor_D', 'Bhaluahi_D', 'MsmcyDPP_D',
'KcharaRD_D',
'Cochin_L', 'CourtDPP_D', 'SirsaDPP_D', 'Ptrlbunk_D',
'NatunDPP_D',
'Enayetpr_D', 'BsnoiHPL_D', 'Idgah_P', 'Chandigarh',
'ColnyDPP_D',
'Pettah_D', 'Mylapore', 'NaturDPP_D', 'UttarDPP_D',
'MdnprDPP_D',
'Kanakpur_D', 'Salap_DC', 'Idgah_L', 'Kolar Mandakni',
'SohnaRd_D',
'NagplDPP_D', 'KeranDPP_D', 'BnkrGate_D', 'SndbrDPP_D',
'RoopNgr_D', 'Jharia_DC', 'Jabalpur', 'NadthiCx_D',
'Sangetha_D',
'Ramnagar_D', 'WamanDPP_D', 'DiyoDPP_D', 'JJCpxDPP_D',

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'RwStnDPP_D', 'Ricco_D', 'Poonamallee_L', 'Umargaon_DC',
'BalibDPP_D', 'Kadtmpty_D', 'KotyamRD_D', 'MemariRD_D',
'Srirmpur_D', 'Central_L_8', 'FulbaDPP_D', 'SukntDPP_D',
'Kondapur_D', 'VUNagar_DC', 'Prjapati_D', 'EtawahDPP_D',
'UdaynDPP_D', 'DibngVly_D', 'GndhiChk_D', 'Muktsar_D',
'Ghansoli_DC', 'Kovaipudur_Dc', 'Lajwanti', 'Central_H_4',
'BrezeDPP_D', 'Rjndpara_D', 'BazarDPP_D', 'MotiDPP_D',
'MrgnjDPP_D', 'Jaripatk_DC', 'Sarjapur_D', 'Kothanur_L',
'AshkngRd_D', 'JiswlDPP_D', 'West_Dc', 'BargaDPP_D',
'SbhRDDPP_D',
    'Parai_D', 'KhsmiDPP_D', 'ChatidPP_D', 'Bulabeda_D',
'ChtwrDPP_D',
    'RhmgjDPP_D', 'Kooriyad_D', 'Bhandup West_Dc', 'GMndiDPP_D',
    'GurpdDPP_D', 'Kaura_D', 'Bnsibtla_D', 'MjlprDPP_D',
'Varanasi',
    'TilakNgr_D', 'Manchar_D', 'Old', 'ShantiDPP_D', 'Royapuram',
    'DivrsnRd_D', 'SliprDPP_DC', 'RajRdDPP_D', 'KrisnKunj_D',
    'ShivaDPP_D', 'East_D_7', 'Rajpura_D', 'SingCLNY_D',
'CBRoad_D',
    'Sidrd_D', 'Krusphrma_D', 'Karelibaug_DC', 'Rgstr0FC_D',
    'Sanpada_CP', 'Bhilai_DC', 'Nattukal_D', 'AnadiDPP_D',
    'ArickDPP_D', 'VrdhriRD_D'], dtype=object)

de['destination_state'].unique()

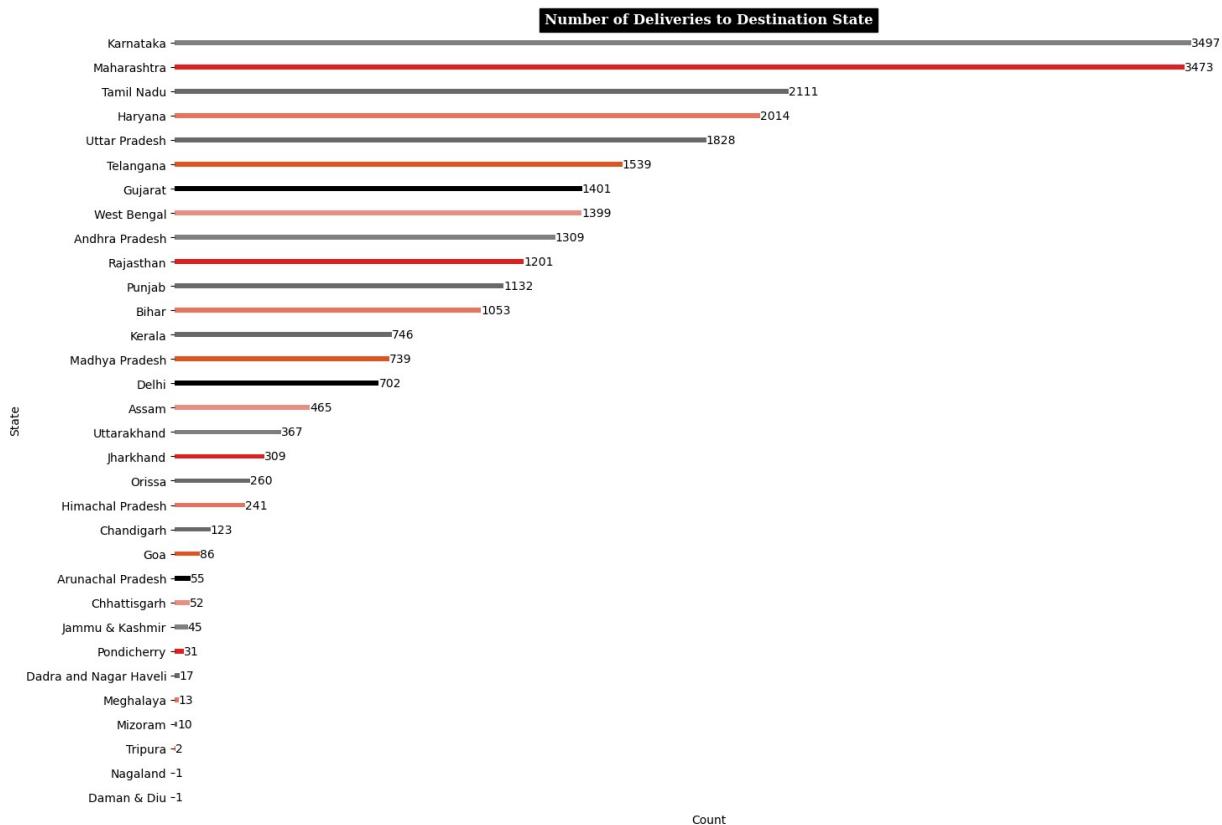
array(['Haryana', 'Uttar Pradesh', 'Karnataka', 'Punjab',
'Maharashtra',
    'Tamil Nadu', 'Gujarat', 'Delhi', 'Andhra Pradesh',
'Telangana',
    'Rajasthan', 'Madhya Pradesh', 'Assam', 'West Bengal',
    'Chandigarh', 'Dadra and Nagar Haveli', 'Orissa',
'Uttarakhand',
    'Bihar', 'Jharkhand', 'Pondicherry', 'Goa', 'Himachal Pradesh',
    'Kerala', 'Arunachal Pradesh', 'Mizoram', 'Chhattisgarh',
    'Jammu & Kashmir', 'Meghalaya', 'Nagaland', 'Tripura',
    'Daman & Diu'], dtype=object)

state_counts =
de['destination_state'].value_counts().to_frame().reset_index()
state_counts.columns = ['State', 'Count']

plt.figure(figsize=(15,10))
a = sns.barplot(y='State', x='Count',
data=state_counts, palette=cp, width=0.2)
a.bar_label(a.containers[0], label_type='edge')
plt.xticks([])
plt.ylabel('State')
plt.xlabel('Count')
plt.title('Number of Deliveries to Destination State', fontsize=12, fontfamily='serif', fontweight='bold', backgroundcolor='white')

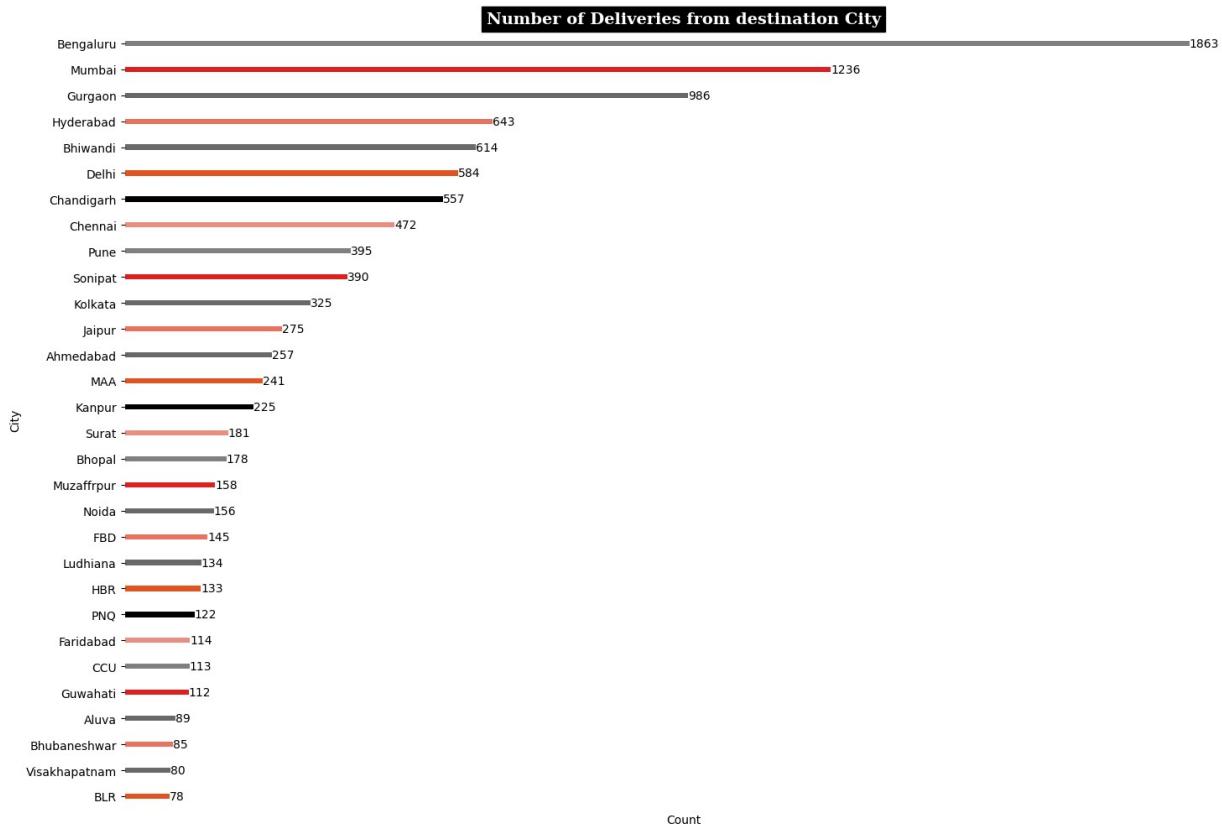
```

```
r='k',color='w')
plt.tight_layout()
sns.despine(bottom=True, left=True)
plt.show()
```



```
city_counts =
de['destination_city'].value_counts().to_frame().reset_index()[:30]
city_counts.columns = ['City', 'Count']

plt.figure(figsize=(15,10))
a = sns.barplot(y='City', x='Count',
data=city_counts, palette=cp, width=0.2)
a.bar_label(a.containers[0], label_type='edge')
plt.xticks([])
plt.ylabel('City')
plt.xlabel('Count')
plt.title('Number of Deliveries from destination  
City', fontsize=14, fontfamily='serif', fontweight='bold', backgroundcolor='k', color='w')
plt.tight_layout()
sns.despine(bottom=True, left=True)
plt.show()
```



Insights:

Destination State

- States like **Karnataka, Maharashtra, Tamil Nadu, Haryana, and Uttar Pradesh** where maximum packages are received in this month indicating significant engagement.

Destination City

- Cities like **Bengaluru, Mumbai, Gurgaon, Bhiwandi, Hyderabad, Delhi** where the major no.of booking are received.

```
np.set_printoptions(threshold=np.inf)

de['corridor'] = de['source_name'] + ' <--> ' + de['destination_name']
de['corridor'].value_counts()

corridor
Bangalore_Nelmngla_H (Karnataka) <--> Bengaluru_KGAirprt_HB
(Karnataka) 151
Bangalore_Nelmngla_H (Karnataka) <--> Bengaluru_Bomsndra_HB
(Karnataka) 127
Bengaluru_Bomsndra_HB (Karnataka) <--> Bengaluru_KGAirprt_HB
(Karnataka) 121
Bengaluru_KGAirprt_HB (Karnataka) <--> Bangalore_Nelmngla_H
(Karnataka) 108
Pune_Tathawde_H (Maharashtra) <--> Bhiwandi_Mankoli_HB (Maharashtra)
107
```

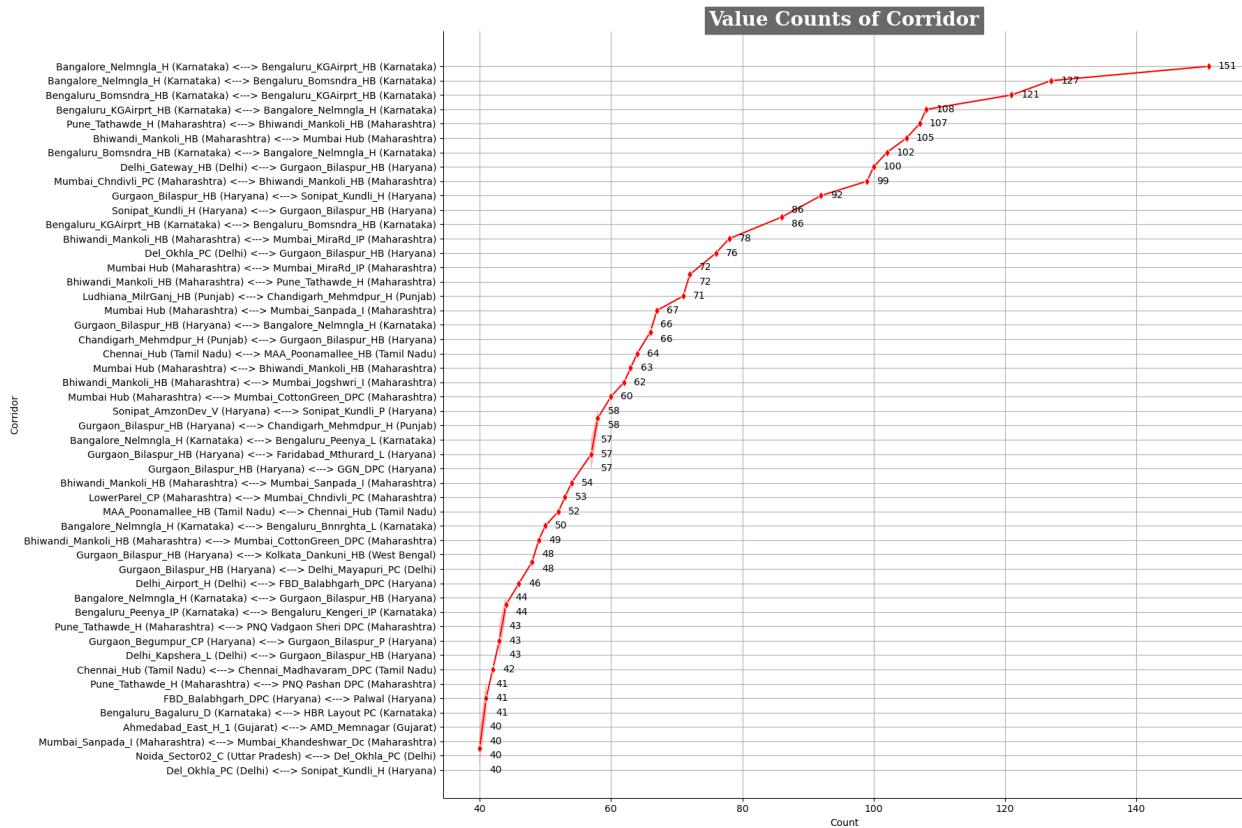
```
...
Ongole_SubhVRTL_I (Andhra Pradesh) <--> Kandukur_LICOffce_D (Andhra
Pradesh) 1
Madnapalle_PngnrRd_D (Andhra Pradesh) <--> Palamaner_Lakshmi_D
(Andhra Pradesh) 1
Dharmavram_SaiNgr_D (Andhra Pradesh) <--> Kadiri_GVManu_D (Andhra
Pradesh) 1
Baharampur_Chuanpur_I (West Bengal) <--> Chapra_NagarDPP_D (West
Bengal) 1
Jaipur_NgrNigam_DC (Rajasthan) <--> Jaipur_Central_D_1 (Rajasthan)
1
Name: count, Length: 2741, dtype: int64

corridor_counts = de['corridor'].value_counts()[:50]

plt.figure(figsize=(18,12))
#corridor_counts.plot(kind='line', marker='d', color='r')
sns.lineplot(y=corridor_counts.index, x=corridor_counts.values,
marker='d', color='r')
plt.title('Value Counts of
Corridor', fontsize=20, fontfamily='serif', fontweight='bold', backgroundc
olor='dimgrey', color='w')
plt.ylabel('Corridor')
plt.xlabel('Count')
plt.tight_layout()
sns.despine()
plt.grid(True)

for i, count in enumerate(corridor_counts.values):
    plt.text(count+1.5, corridor_counts.index[i], str(count),
ha='left', va='center')

plt.show()
```



Insights:

- The route between **Bangalore_Nelamangala_H** to **Bengaluru_KGAirport_HB, Bengaluru_Bomsndra_HB** sees the highest package volume, with 151 and 127 packages sent respectively.
- Bengaluru_Bommasaundra_HB** to **Bengaluru_KGAirport_HB** is also popular, with 121 packages sent.
- Bengaluru_KGAirport_HB** to **Bangalore_Nelamangala_H** has moderate activity, with 108 packages sent.
- 1. The data indicates Bengaluru's importance as a transportation hub **Corridor** within **Karnataka**, handling significant package traffic.

```
de['state_corridor'] = de['source_state']+---+de['source_city'] +'  
<---> '+ de['destination_state']+---+de['destination_city']  
de['state_corridor'].value_counts()
```

state_corridor	
Karnataka--Bengaluru <---> Karnataka--Bengaluru	1413
Maharashtra--Mumbai <---> Maharashtra--Mumbai	622
Maharashtra--Bhiwandi <---> Maharashtra--Mumbai	512
Maharashtra--Mumbai <---> Maharashtra--Bhiwandi	345
Telangana--Hyderabad <---> Telangana--Hyderabad	316
...	
Gujarat--Jetpur <---> Gujarat--Dhoraji	1
Andhra Pradesh--Anakapalle <---> Andhra Pradesh--Visakhapatnam	1

```

Andhra Pradesh--Narsiptnm <---> Andhra Pradesh--Anakapalle 1
West Bengal--MirzapurWB <---> West Bengal--Kolkata 1
Uttar Pradesh--Anandnagar <---> Uttar Pradesh--Gorakhpur 1
Name: count, Length: 2302, dtype: int64

```

```

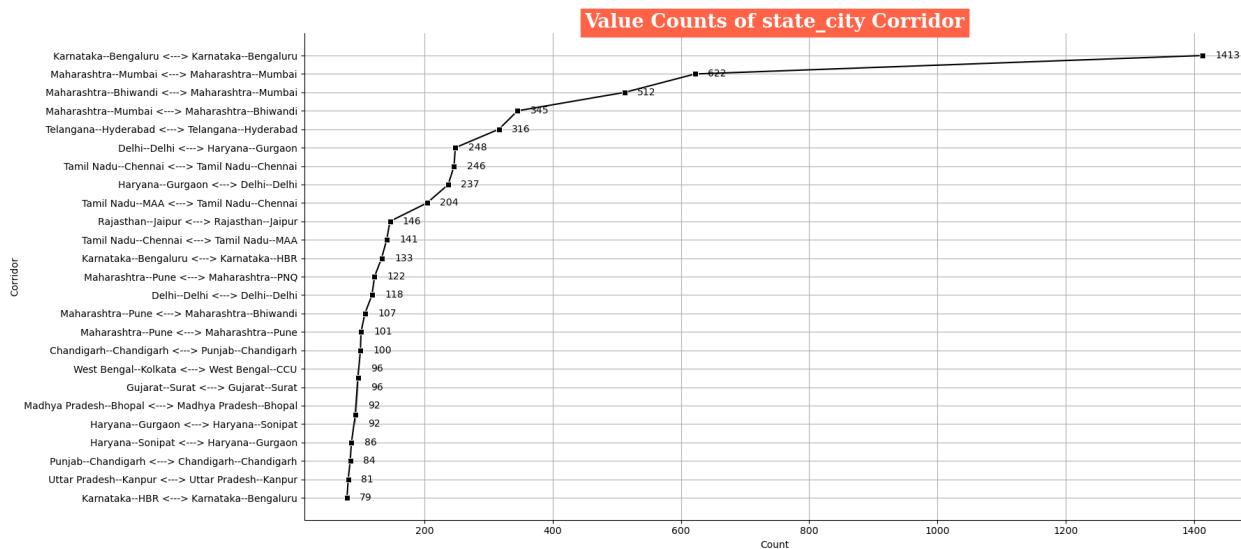
state_corridor_counts = de['state_corridor'].value_counts()[:25]

plt.figure(figsize=(18,8))
sns.lineplot(y=state_corridor_counts.index,
x=state_corridor_counts.values, marker='s', color='k')
plt.title('Value Counts of state_city Corridor', fontsize=20, fontfamily='serif', fontweight='bold', backgroundcolor='tomato', color='w')
plt.ylabel('Corridor')
plt.xlabel('Count')
plt.tight_layout()
sns.despine()
plt.grid(True)

for i, count in enumerate(state_corridor_counts.values):
    plt.text(count+20, state_corridor_counts.index[i], str(count),
ha='left', va='center')

plt.show()

```



```

de['city_corridor'] = de['source_city']+'''+de['source_place'] +'
<---> '+ de['destination_city']+'''+de['destination_place']
display(de['city_corridor'].value_counts())

city_corridor
Bengaluru--Nelmngla_H <---> Bengaluru--KGAirprt_HB 151
Bengaluru--Nelmngla_H <---> Bengaluru--Bomsndra_HB 127
Bengaluru--Bomsndra_HB <---> Bengaluru--KGAirprt_HB 121

```

```

Bengaluru--KGAirport_HB <---> Bengaluru--Nelmgla_H      108
Pune--Tathawde_H <---> Bhiwandi--Mankoli_H          107
...
Ongole--SubhVRTL_I <---> Kandukur--LICOffce_D        1
Madnapalle--PngnrRd_D <---> Palamaner--Lakshmi_D      1
Dharmavram--SaiNgr_D <---> Kadiri--GVManu_D          1
Baharampur--Chuanpur_I <---> Chapra--NagarDPP_D       1
Jaipur--NgrNigam_DC <---> Jaipur--Central_D_1         1
Name: count, Length: 2741, dtype: int64

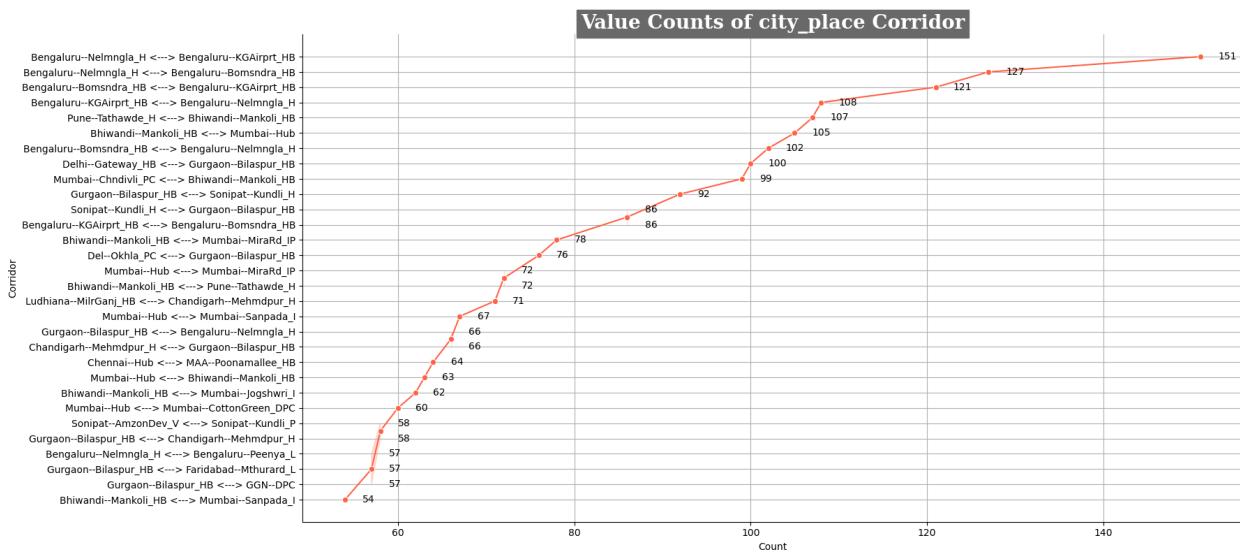
city_corridor_counts = de['city_corridor'].value_counts()[:30]

plt.figure(figsize=(18,8))
sns.lineplot(y=city_corridor_counts.index,
x=city_corridor_counts.values, marker='o', color='tomato')
plt.title('Value Counts of city_place Corridor', fontsize=20, fontfamily='serif', fontweight='bold', backgroundcolor='dimgray', color='w')
plt.ylabel('Corridor')
plt.xlabel('Count')
plt.tight_layout()
sns.despine()
plt.grid(True)

for i, count in enumerate(city_corridor_counts.values):
    plt.text(count+2, city_corridor_counts.index[i], str(count), ha='left', va='center')

plt.show()

```



Insights:

- Maharashtra, Karnataka, Haryana, and Tamil Nadu serve as key starting and ending locations for delivery services.

- Mumbai, Gurgaon, Delhi, and Bengaluru are major metropolitan centers from where many deliveries originate.
- A large proportion of nationwide deliveries are destined for Mumbai, Bengaluru, Gurgaon, and Delhi.

```
# 4. Extracting features like month, year, day, etc. from
Trip_creation_time
de['trip_creation_month'] = de['trip_creation_time'].dt.month
de['trip_creation_year'] = de['trip_creation_time'].dt.year
de['trip_creation_day'] = de['trip_creation_time'].dt.day
de['trip_creation_hour'] = de['trip_creation_time'].dt.hour
de['trip_creation_weekday'] = de['trip_creation_time'].dt.weekday
de['trip_creation_week'] =
de['trip_creation_time'].dt.isocalendar().week
de

segment_key \
0    trip-153671041653548748+IND209304AAA+IND000000ACB
1    trip-153671041653548748+IND462022AAA+IND209304AAA
2    trip-153671042288605164+IND561203AAB+IND562101AAA
3    trip-153671042288605164+IND572101AAA+IND561203AAB
4    trip-153671043369099517+IND000000ACB+IND160002AAC
...
26217   trip-153861115439069069+IND628204AAA+IND627657AAA
26218   trip-153861115439069069+IND628613AAA+IND627005AAA
26219   trip-153861115439069069+IND628801AAA+IND628204AAA
26220   trip-153861118270144424+IND583119AAA+IND583101AAA
26221   trip-153861118270144424+IND583201AAA+IND583119AAA

trip_uuid      data route_type \
0    trip-153671041653548748  training      FTL
1    trip-153671041653548748  training      FTL
2    trip-153671042288605164  training    Carting
3    trip-153671042288605164  training    Carting
4    trip-153671043369099517  training      FTL
...
26217   trip-153861115439069069      test    Carting
26218   trip-153861115439069069      test    Carting
26219   trip-153861115439069069      test    Carting
26220   trip-153861118270144424      test      FTL
26221   trip-153861118270144424      test      FTL

trip_creation_time
source_name \
0    2018-09-12 00:00:16.535741  Kanpur_Central_H_6 (Uttar Pradesh)
1    2018-09-12 00:00:16.535741  Bhopal_Trnsport_H (Madhya Pradesh)
2    2018-09-12 00:00:22.886430  Doddablpur_ChikaDPP_D (Karnataka)
3    2018-09-12 00:00:22.886430        Tumkur_Veersagr_I (Karnataka)
```

	od_start_time	destination_name
4	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)
...
26217	2018-10-03 23:59:14.390954	Tirchchndr_Shnmgrpm_D (Tamil Nadu)
26218	2018-10-03 23:59:14.390954	Peikulam_SriVnktpm_D (Tamil Nadu)
26219	2018-10-03 23:59:14.390954	Eral_Busstand_D (Tamil Nadu)
26220	2018-10-03 23:59:42.701692	Sandur_WrdN1DPP_D (Karnataka)
26221	2018-10-03 23:59:42.701692	Hospet (Karnataka)
...
0	2018-09-12 16:39:46.858469	Gurgaon_Bilaspur_HB (Haryana) 2018-09-12
1	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)
2	2018-09-12 02:03:09.655591	Chikblapur_ShntiSgr_D (Karnataka)
3	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)
4	2018-09-14 03:40:17.106733	Chandigarh_Mehmdpur_H (Punjab)
...
26217	2018-10-04 02:29:04.272194	Thisayanvilai_UdnkdiRD_D (Tamil Nadu)
26218	2018-10-04 04:16:39.894872	Tirunelveli_VdkkuSrt_I (Tamil Nadu)
26219	2018-10-04 01:44:53.808000	Tirchchndr_Shnmgrpm_D (Tamil Nadu)
26220	2018-10-04 03:58:40.726547	Bellary_Dc (Karnataka)
26221	2018-10-04 02:51:44.712656	Sandur_WrdN1DPP_D (Karnataka)
...
0	2018-09-13 13:40:23.123744	od_end_time start_scan_to_end_scan \ 1260.0
1	2018-09-12 16:39:46.858469	999.0
2	2018-09-12 03:01:59.598855	58.0
3	2018-09-12 02:03:09.655591	122.0
4	2018-09-14 17:34:55.442454	834.0
...
26217	2018-10-04 03:31:11.183797	62.0
26218	2018-10-04 05:47:45.162682	91.0

26219	2018-10-04	02:29:04.272194		44.0
26220	2018-10-04	08:46:09.166940		287.0
26221	2018-10-04	03:58:40.726547		66.0
<hr/>				
osrm_distance \		actual_distance_to_destination	actual_time	osrm_time
0		383.759155	732.0	329.0
446.549591				
1		440.973694	830.0	388.0
544.802673				
2		24.644020	47.0	26.0
28.199400				
3		48.542889	96.0	42.0
56.911598				
4		237.439606	611.0	212.0
281.210907				
...	
...				
26217		33.627182	51.0	41.0
42.521301				
26218		33.673836	90.0	48.0
40.608002				
26219		12.661944	30.0	14.0
16.018499				
26220		40.546738	233.0	42.0
52.530300				
26221		25.534794	42.0	26.0
28.048401				
<hr/>				
segment_osrm_distance \		segment_actual_time	segment_osrm_time	
0		728.0	534.0	670.620483
1		820.0	474.0	649.852783
2		46.0	26.0	28.199501
3		95.0	39.0	55.989899
4		608.0	231.0	317.740784
...	
...				
26217		49.0	42.0	42.143101
26218		89.0	77.0	78.586899
26219		29.0	14.0	16.018400
26220		233.0	42.0	52.530300

26221	41.0	25.0	28.048401
-------	------	------	-----------

	segment_actual_time_sum	segment_osrm_time_sum	\
0	728.0	534.0	
1	820.0	474.0	
2	46.0	26.0	
3	95.0	39.0	
4	608.0	231.0	
...	
26217	49.0	42.0	
26218	89.0	77.0	
26219	29.0	14.0	
26220	233.0	42.0	
26221	41.0	25.0	

od_time_diff_hour	segment_osrm_distance_sum	od_total_time
0	670.620483	0 days 21:00:36.265275
21.010074		
1	649.852783	0 days 16:39:30.322728
16.658423		
2	28.199501	0 days 00:58:49.943264
0.980540		
3	55.989899	0 days 02:02:46.769161
2.046325		
4	317.740784	0 days 13:54:38.335721
13.910649		
...
...
26217	42.143101	0 days 01:02:06.911603
1.035253		
26218	78.586899	0 days 01:31:05.267810
1.518130		
26219	16.018400	0 days 00:44:10.464194
0.736240		
26220	52.530300	0 days 04:47:28.440393
4.791233		
26221	28.048401	0 days 01:06:56.013891
1.115559		

	source_city	source_place	source_state	destination_city	\
0	Kanpur	Central_H_6	Uttar Pradesh	Gurgaon	
1	Bhopal	Trnsport_H	Madhya Pradesh	Kanpur	
2	Doddablpur	ChikaDPP_D	Karnataka	Chikblapur	
3	Tumkur	Veersagr_I	Karnataka	Doddablpur	
4	Gurgaon	Bilaspur_HB	Haryana	Chandigarh	
...	
26217	Tirchchndr	Shnmgprm_D	Tamil Nadu	Thisayanvilai	

26218	Peikulam	SriVnktpm_D	Tamil Nadu	Tirunelveli
26219	Eral	Busstand_D	Tamil Nadu	Tirchchndr
26220	Sandur	WrdN1DPP_D	Karnataka	Bellary
26221	Hospet	Hospet	Karnataka	Sandur

	destination_place	destination_state	\
0	Bilaspur_HB	Haryana	
1	Central_H_6	Uttar Pradesh	
2	ShntiSgr_D	Karnataka	
3	ChikaDPP_D	Karnataka	
4	Mehmdpur_H	Punjab	
...	
26217	UdnkdiRD_D	Tamil Nadu	
26218	VdkkuSrt_I	Tamil Nadu	
26219	Shnmgprm_D	Tamil Nadu	
26220	Dc	Karnataka	
26221	WrdN1DPP_D	Karnataka	

	corridor	\
0	Kanpur_Central_H_6 (Uttar Pradesh)	<----> Gurgaon
1	Bhopal_Trnsport_H (Madhya Pradesh)	<----> Kanpur
2	Doddablpur_ChikaDPP_D (Karnataka)	<----> Chikballapur
3	Tumkur_Veersagr_I (Karnataka)	<----> Doddablpur
4	Gurgaon_Bilaspur_HB (Haryana)	<----> Chandigarh
...
26217	Tirchchndr_Shnmgprm_D (Tamil Nadu)	<----> Thisai
26218	Peikulam_SriVnktpm_D (Tamil Nadu)	<----> Tirunelveli
26219	Eral_Busstand_D (Tamil Nadu)	<----> Tirchchndr
26220	Sandur_WrdN1DPP_D (Karnataka)	<----> Bellary_Dc
26221	Hospet (Karnataka)	<----> Sandur_WrdN1DPP_D (Karnataka)

	state_corridor	\
0	Uttar Pradesh--Kanpur	<----> Haryana--Gurgaon
1	Madhya Pradesh--Bhopal	<----> Uttar Pradesh--Kanpur
2	Karnataka--Doddablpur	<----> Karnataka--Chikballapur
3	Karnataka--Tumkur	<----> Karnataka--Doddablpur
4	Haryana--Gurgaon	<----> Punjab--Chandigarh
...
26217	Tamil Nadu--Tirchchndr	<----> Tamil Nadu--Thisai
26218	Tamil Nadu--Peikulam	<----> Tamil Nadu--Tirunelveli
26219	Tamil Nadu--Eral	<----> Tamil Nadu--Tirchchndr
26220	Karnataka--Sandur	<----> Karnataka--Bellary
26221	Karnataka--Hospet	<----> Karnataka--Sandur

	city_corridor
trip_creation_month \	
0	Kanpur--Central_H_6 <----> Gurgaon--Bilaspur_HB
9	
1	Bhopal--Trnsport_H <----> Kanpur--Central_H_6
9	

```

2      Doddablpur--ChikaDPP_D <---> Chikblapur--Shnti...
9
3      Tumkur--Veersagr_I <---> Doddablpur--ChikaDPP_D
9
4      Gurgaon--Bilaspur_HB <---> Chandigarh--Mehmdpur_H
9
...
...
26217  Tirchchndr--Shnmgprm_D <---> Thisayanvilai--Ud...
10
26218  Peikulam--SriVnktpm_D <---> Tirunelveli--Vdkku...
10
26219      Eral--Busstand_D <---> Tirchchndr--Shnmgprm_D
10
26220              Sandur--WrdN1DPP_D <---> Bellary--Dc
10
26221      Hospet--Hospet <---> Sandur--WrdN1DPP_D
10

```

	trip_creation_year	trip_creation_day	trip_creation_hour	\
0	2018	12	0	
1	2018	12	0	
2	2018	12	0	
3	2018	12	0	
4	2018	12	0	
...
26217	2018	3	23	
26218	2018	3	23	
26219	2018	3	23	
26220	2018	3	23	
26221	2018	3	23	

	trip_creation_weekday	trip_creation_week
0	2	37
1	2	37
2	2	37
3	2	37
4	2	37
...
26217	2	40
26218	2	40
26219	2	40
26220	2	40
26221	2	40

[26222 rows x 37 columns]

In-Depth Analysis

```
new_df = de.copy()

new_df.columns

Index(['segment_key', 'trip_uuid', 'data', 'route_type',
       'trip_creation_time',
       'source_name', 'destination_name', 'od_start_time',
       'od_end_time',
       'start_scan_to_end_scan', 'actual_distance_to_destination',
       'actual_time', 'osrm_time', 'osrm_distance',
       'segment_actual_time',
       'segment_osrm_time', 'segment_osrm_distance',
       'segment_actual_time_sum',
       'segment_osrm_time_sum', 'segment_osrm_distance_sum',
       'od_total_time',
       'od_time_diff_hour', 'source_city', 'source_place',
       'source_state',
       'destination_city', 'destination_place', 'destination_state',
       'corridor', 'state_corridor', 'city_corridor',
       'trip_creation_month',
       'trip_creation_year', 'trip_creation_day',
       'trip_creation_hour',
       'trip_creation_weekday', 'trip_creation_week'],
      dtype='object')

new_df.sample(2)

           segment_key \
3330  trip-153694740553026744+IND574104AAA+IND574216AAA
3755  trip-153696604384005633+IND507117AAB+IND507303AAA

           trip_uuid     data route_type
trip_creation_time \
3330  trip-153694740553026744  training   Carting 2018-09-14
17:50:05.530477
3755  trip-153696604384005633  training        FTL 2018-09-14
23:00:43.840397

           source_name
destination_name \
3330  Karkala_MarketRd_D (Karnataka)  Dharmasthala_Belngdi_D
(Karnataka)
3755  Manuguru_AskNagar_D (Telangana)  Sathupally_VidyaNGR_D
(Telangana)

           od_start_time          od_end_time \
3330  2018-09-15 02:48:16.030062  2018-09-15 04:38:56.729715
3755  2018-09-15 04:15:30.426079  2018-09-15 07:28:59.609574
```

```

      start_scan_to_end_scan  actual_distance_to_destination
actual_time \
3330          110.0                  43.015263
88.0
3755          193.0                  79.276848
177.0

      osrm_time  osrm_distance  segment_actual_time  segment_osrm_time
\
3330        47.0      54.231701           86.0          45.0
3755        92.0      121.918297          176.0         139.0

      segment_osrm_distance  segment_actual_time_sum
segment_osrm_time_sum \
3330          54.231598           86.0
45.0
3755          114.664200          176.0
139.0

      segment_osrm_distance_sum          od_total_time
od_time_diff_hour \
3330          54.231598 0 days 01:50:40.699653
1.844639
3755          114.664200 0 days 03:13:29.183495
3.224773

      source_city source_place source_state destination_city
destination_place \
3330      Karkala   MarketRd_D    Karnataka       Dharmsthal
Belngdi_D
3755      Manuguru  AskNagar_D   Telangana        Sathupally
VidyaNGR_D

      destination_state
corridor \
3330      Karnataka Karkala_MarketRd_D (Karnataka) <-->
Dharmsthal...
3755      Telangana  Manuguru_AskNagar_D (Telangana) <-->
Sathupal...

      state_corridor \
3330  Karnataka--Karkala <---> Karnataka--Dharmsthal
3755  Telangana--Manuguru <---> Telangana--Sathupally

      city_corridor
trip_creation_month \
3330  Karkala--MarketRd_D <---> Dharmsthal--Belngdi_D
9

```

```
3755 Manuguru--AskNagar_D <---> Sathupally--VidyaNGR_D
9
```

	trip_creation_year	trip_creation_day	trip_creation_hour	\
3330	2018	14	17	
3755	2018	14	23	

	trip_creation_weekday	trip_creation_week
3330	4	37
3755	4	37

```
create_trip_dict={  
    'data' : 'first',  
    'route_type' : 'first',  
    'od_start_time':'first',  
    'od_end_time':'last',  
    'od_time_diff_hour' : 'sum',  
    'trip_creation_time' : 'first',  
    'trip_creation_month' : 'first',  
    'trip_creation_year' : 'first',  
    'trip_creation_day' : 'first',  
    'trip_creation_hour' : 'first',  
    'trip_creation_weekday' : 'first',  
    'trip_creation_week' : 'first',  
    'start_scan_to_end_scan' : 'sum',  
    'actual_distance_to_destination' : 'sum',  
    'actual_time' : 'sum',  
    'osrm_time' : 'sum',  
    'osrm_distance' : 'sum',  
    'segment_actual_time': 'sum',  
    'segment_osrm_time': 'sum',  
    'segment_osrm_distance': 'sum',  
    'segment_actual_time_sum': 'sum',  
    'segment_osrm_time_sum': 'sum',  
    'segment_osrm_distance_sum': 'sum',  
    'source_name': 'first',  
    'source_city':'first',  
    'source_state':'first',  
    'source_place':'first',  
    'destination_name': 'first',  
    'destination_city':'first',  
    'destination_state':'first',  
    'destination_place':'first',  
    'corridor':'first',  
    'state_corridor':'first',  
    'city_corridor':'first'  
}  
trip_agg_df =
```

```
new_df.groupby('trip_uuid').agg(create_trip_dict).reset_index()  
trip_agg_df
```

	trip_uuid	data	route_type	\
0	trip-153671041653548748	training	FTL	
1	trip-153671042288605164	training	Carting	
2	trip-153671043369099517	training	FTL	
3	trip-153671046011330457	training	Carting	
4	trip-153671052974046625	training	FTL	
...
14782	trip-153861095625827784	test	Carting	
14783	trip-153861104386292051	test	Carting	
14784	trip-153861106442901555	test	Carting	
14785	trip-153861115439069069	test	Carting	
14786	trip-153861118270144424	test	FTL	
	od_start_time		od_end_time	\
0	2018-09-12 16:39:46.858469	2018-09-12 16:39:46.858469		
1	2018-09-12 02:03:09.655591	2018-09-12 02:03:09.655591		
2	2018-09-14 03:40:17.106733	2018-09-14 03:40:17.106733		
3	2018-09-12 00:01:00.113710	2018-09-12 01:41:29.809822		
4	2018-09-12 00:02:09.740725	2018-09-12 03:54:43.114421		
...
14782	2018-10-03 23:55:56.258533	2018-10-04 06:41:25.409035		
14783	2018-10-03 23:57:23.863155	2018-10-04 00:57:59.294434		
14784	2018-10-04 02:51:27.075797	2018-10-04 02:51:27.075797		
14785	2018-10-03 23:59:14.390954	2018-10-04 02:29:04.272194		
14786	2018-10-04 03:58:40.726547	2018-10-04 03:58:40.726547		
	od_time_diff_hour		trip_creation_time	
trip_creation_month	\			
0	37.668497	2018-09-12 00:00:16.535741		
9				
1	3.026865	2018-09-12 00:00:22.886430		
9				
2	65.572709	2018-09-12 00:00:33.691250		
9				
3	1.674916	2018-09-12 00:01:00.113710		
9				
4	11.972484	2018-09-12 00:02:09.740725		
9				
...
14782	4.300482	2018-10-03 23:55:56.258533		
10				
14783	1.009842	2018-10-03 23:57:23.863155		
10				
14784	7.035331	2018-10-03 23:57:44.429324		
10				
14785	5.808548	2018-10-03 23:59:14.390954		

```

10
14786      5.906793 2018-10-03 23:59:42.701692
10

    trip_creation_year  trip_creation_day  trip_creation_hour \
0            2018                  12                  0
1            2018                  12                  0
2            2018                  12                  0
3            2018                  12                  0
4            2018                  12                  0
...
14782        ...                  ...                  ...
14783        2018                  3                  23
14784        2018                  3                  23
14785        2018                  3                  23
14786        2018                  3                  23

    trip_creation_weekday  trip_creation_week
start_scan_to_end_scan \
0                      2                  37
2259.0
1                      2                  37
180.0
2                      2                  37
3933.0
3                      2                  37
100.0
4                      2                  37
717.0
...
...
14782        ...                  ...                  ...
14783        2018                  2                  40
257.0
14784        2018                  2                  40
60.0
14785        2018                  2                  40
421.0
14786        2018                  2                  40
353.0

    actual_distance_to_destination  actual_time  osrm_time
osrm_distance \
0                      824.732849      1562.0      717.0
991.352295
1                      73.186905      143.0       68.0
85.111000
2                      1927.404297     3347.0     1740.0
2354.066650

```

3	17.175274	59.0	15.0
19.680000			
4	127.448502	341.0	117.0
146.791794			
...
...
14782	57.762333	83.0	62.0
73.462997			
14783	15.513784	21.0	12.0
16.088200			
14784	38.684837	282.0	48.0
58.903702			
14785	134.723831	264.0	179.0
171.110306			
14786	66.081528	275.0	68.0
80.578705			
segment_actual_time segment_osrm_time			
segment_osrm_distance \			
0	1548.0	1008.0	1320.473267
1	141.0	65.0	84.189400
2	3308.0	1941.0	2545.267822
3	59.0	16.0	19.876600
4	340.0	115.0	146.791901
...
14782	82.0	62.0	64.855103
14783	21.0	11.0	16.088299
14784	281.0	88.0	104.886597
14785	258.0	221.0	223.532394
14786	274.0	67.0	80.578705
segment_actual_time_sum segment_osrm_time_sum \			
0	1548.0	1008.0	
1	141.0	65.0	
2	3308.0	1941.0	
3	59.0	16.0	
4	340.0	115.0	
...	
14782	82.0	62.0	

14783	21.0	11.0	
14784	281.0	88.0	
14785	258.0	221.0	
14786	274.0	67.0	
	segment_osrm_distance_sum	source_name	
\			
0	1320.473267	Kanpur_Central_H_6 (Uttar Pradesh)	
1	84.189400	Doddablpur_ChikaDPP_D (Karnataka)	
2	2545.267822	Gurgaon_Bilaspur_HB (Haryana)	
3	19.876600	Mumbai Hub (Maharashtra)	
4	146.791901	Bellary_Dc (Karnataka)	
	
...	
14782	64.855103	Chandigarh_Mehmdpur_H (Punjab)	
14783	16.088299	FBD_Balabhgarh_DPC (Haryana)	
14784	104.886597	Kanpur_GovndNgr_DC (Uttar Pradesh)	
14785	223.532394	Tirunelveli_VdkkuSrt_I (Tamil Nadu)	
14786	80.578705	Sandur_WrdN1DPP_D (Karnataka)	
	source_city	source_state	source_place \
0	Kanpur	Uttar Pradesh	Central_H_6
1	Doddablpur	Karnataka	ChikaDPP_D
2	Gurgaon	Haryana	Bilaspur_HB
3	Mumbai	Maharashtra	Hub
4	Bellary	Karnataka	Dc

14782	Chandigarh	Punjab	Mehmdpur_H
14783	FBD	Haryana	Balabhgarh_DPC
14784	Kanpur	Uttar Pradesh	GovndNgr_DC
14785	Tirunelveli	Tamil Nadu	VdkkuSrt_I
14786	Sandur	Karnataka	WrdN1DPP_D
	destination_name	destination_city	
destination_state \			
0	Gurgaon_Bilaspur_HB (Haryana)	Gurgaon	
Haryana			
1	Chikblapur_ShntiSgr_D (Karnataka)	Chikblapur	
Karnataka			
2	Chandigarh_Mehmdpur_H (Punjab)	Chandigarh	
Punjab			

```

3           Mumbai_MiraRd_IP (Maharashtra)           Mumbai
Maharashtra
4           Hospet (Karnataka)                     Hospet
Karnataka
...
...
14782          Zirakpur_DC (Punjab)             Zirakpur
Punjab
14783      Faridabad_Blbgarh_DC (Haryana)       Faridabad
Haryana
14784  Kanpur_Central_H_6 (Uttar Pradesh)        Kanpur   Uttar
Pradesh
14785      Eral_Busstand_D (Tamil Nadu)          Eral
Tamil Nadu
14786          Bellary_Dc (Karnataka)            Bellary
Karnataka

    destination_place
corridor \
0           Bilaspur_HB  Kanpur_Central_H_6 (Uttar Pradesh) <-->
Gurga...
1           ShntiSgr_D  Doddablpur_ChikaDPP_D (Karnataka) <-->
Chikbl...
2           Mehmdpur_H  Gurgaon_Bilaspur_HB (Haryana) <-->
Chandigarh...
3           MiraRd_IP   Mumbai Hub (Maharashtra) <-->
Mumbai_MiraRd_I...
4           Hospet     Bellary_Dc (Karnataka) <--> Hospet
(Karnataka)
...
...
14782          DC  Chandigarh_Mehmdpur_H (Punjab) <-->
Zirakpur_...
14783      Blbgarh_DC  FBD_Balabhgarh_DPC (Haryana) <-->
Faridabad_B...
14784      Central_H_6  Kanpur_GovndNgr_DC (Uttar Pradesh) <-->
Kanpu...
14785      Busstand_D   Tirunelveli_VdkkuSrt_I (Tamil Nadu) <-->
Eral...
14786          Dc  Sandur_WrdN1DPP_D (Karnataka) <-->
Bellary_Dc...

    state_corridor \
0           Uttar Pradesh--Kanpur <--> Haryana--Gurgaon
1           Karnataka--Doddablpur <--> Karnataka--Chiklapur
2           Haryana--Gurgaon <--> Punjab--Chandigarh
3           Maharashtra--Mumbai <--> Maharashtra--Mumbai
4           Karnataka--Bellary <--> Karnataka--Hospet
...

```

```

14782      Punjab--Chandigarh <---> Punjab--Zirakpur
14783          Haryana--FBD <---> Haryana--Faridabad
14784  Uttar Pradesh--Kanpur <---> Uttar Pradesh--Kanpur
14785    Tamil Nadu--Tirunelveli <---> Tamil Nadu--Eral
14786      Karnataka--Sandur <---> Karnataka--Bellary

```

	city_corridor
0	Kanpur--Central_H_6 <---> Gurgaon--Bilaspur_HB
1	Doddablpur--ChikaDPP_D <---> Chikblapur--Shnti...
2	Gurgaon--Bilaspur_HB <---> Chandigarh--Mehmdpur_H
3	Mumbai--Hub <---> Mumbai--MiraRd_IP
4	Bellary--Dc <---> Hospet--Hospet
...	...
14782	Chandigarh--Mehmdpur_H <---> Zirakpur--DC
14783	FBD--Balabhgarh_DPC <---> Faridabad--Blbgarh_DC
14784	Kanpur--GovndNgr_DC <---> Kanpur--Central_H_6
14785	Tirunelveli--VdkkuSrt_I <---> Eral--Busstand_D
14786	Sandur--WrdN1DPP_D <---> Bellary--Dc

[14787 rows x 35 columns]

```

numerical_columns = trip_agg_df.select_dtypes(include=[np.float32,
np.float64])
numerical_columns

```

	od_time_diff_hour	start_scan_to_end_scan
0	37.668497	2259.0
1	3.026865	180.0
2	65.572709	3933.0
3	1.674916	100.0
4	11.972484	717.0
...
14782	4.300482	257.0
14783	1.009842	60.0
14784	7.035331	421.0
14785	5.808548	347.0
14786	5.906793	353.0

osrm_distance \	actual_distance_to_destination	actual_time	osrm_time
0	824.732849	1562.0	717.0
991.352295			
1	73.186905	143.0	68.0
85.111000			
2	1927.404297	3347.0	1740.0
2354.066650			
3	17.175274	59.0	15.0
19.680000			
4	127.448502	341.0	117.0
146.791794			

...
14782	57.762333	83.0	62.0
73.462997			
14783	15.513784	21.0	12.0
16.088200			
14784	38.684837	282.0	48.0
58.903702			
14785	134.723831	264.0	179.0
171.110306			
14786	66.081528	275.0	68.0
80.578705			
segment_actual_time segment_osrm_time			
segment_osrm_distance \			
0	1548.0	1008.0	1320.473267
1	141.0	65.0	84.189400
2	3308.0	1941.0	2545.267822
3	59.0	16.0	19.876600
4	340.0	115.0	146.791901
14782	82.0	62.0	64.855103
14783	21.0	11.0	16.088299
14784	281.0	88.0	104.886597
14785	258.0	221.0	223.532394
14786	274.0	67.0	80.578705
segment_actual_time_sum segment_osrm_time_sum \			
0	1548.0	1008.0	
1	141.0	65.0	
2	3308.0	1941.0	
3	59.0	16.0	
4	340.0	115.0	
14782	82.0	62.0	
14783	21.0	11.0	
14784	281.0	88.0	
14785	258.0	221.0	
14786	274.0	67.0	

```

    segment_osrm_distance_sum
0                  1320.473267
1                  84.189400
2                  2545.267822
3                  19.876600
4                  146.791901
...
14782             ...
14783             16.088299
14784             104.886597
14785             223.532394
14786             80.578705

[14787 rows x 12 columns]

numerical_columns.describe().T

              count      mean       std
min \
od_time_diff_hour      14787.0   8.840187  10.978880
0.391024
start_scan_to_end_scan 14787.0  529.429016  658.254395
23.000000
actual_distance_to_destination 14787.0  164.090195  305.502808
9.002461
actual_time            14787.0  356.306000  561.517761
9.000000
osrm_time              14787.0  160.990936  271.459229
6.000000
osrm_distance          14787.0  203.887405  370.565460
9.072900
segment_actual_time    14787.0  353.059174  556.364441
9.000000
segment_osrm_time     14787.0  180.511597  314.678741
6.000000
segment_osrm_distance 14787.0  222.705444  416.845642
9.072900
segment_actual_time_sum 14787.0  353.059174  556.364441
9.000000
segment_osrm_time_sum 14787.0  180.511597  314.678741
6.000000
segment_osrm_distance_sum 14787.0  222.705444  416.845642
9.072900

              25%      50%      75% \
od_time_diff_hour      2.494975  4.661846  10.558962
start_scan_to_end_scan 149.000000 279.000000 632.000000
actual_distance_to_destination 22.777099 48.287895 163.591255
actual_time            67.000000 148.000000 367.000000
osrm_time              29.000000 60.000000 168.000000

```

```

osrm_distance           30.756900   65.302795   206.644203
segment_actual_time    66.000000   147.000000   364.000000
segment_osrm_time      30.000000   65.000000   184.000000
segment_osrm_distance  32.578850   69.784203   216.560608
segment_actual_time_sum 66.000000   147.000000   364.000000
segment_osrm_time_sum  30.000000   65.000000   184.000000
segment_osrm_distance_sum 32.578850   69.784203   216.560608

```

	max
od_time_diff_hour	131.642533
start_scan_to_end_scan	7898.000000
actual_distance_to_destination	2186.531738
actual_time	6265.000000
osrm_time	2032.000000
osrm_distance	2840.081055
segment_actual_time	6230.000000
segment_osrm_time	2564.000000
segment_osrm_distance	3523.632324
segment_actual_time_sum	6230.000000
segment_osrm_time_sum	2564.000000
segment_osrm_distance_sum	3523.632324

```
trip_agg_df.describe(include = object).T
```

	count	unique	\
trip_uuid	14787	14787	
source_name	14787	930	
source_city	14787	713	
source_state	14787	29	
source_place	14787	788	
destination_name	14787	1042	
destination_city	14787	851	
destination_state	14787	32	
destination_place	14787	866	
corridor	14787	1737	
state_corridor	14787	1366	
city_corridor	14787	1737	

	top
freq	
trip_uuid	trip-153671041653548748
1	
source_name	Gurgaon_Bilaspur_HB (Haryana)
1052	
source_city	Bengaluru
1700	
source_state	Maharashtra
2714	
source_place	Bilaspur_HB
1052	

```

destination_name          Gurgaon_Bilaspur_HB (Haryana)
745
destination_city          Bengaluru
1633
destination_state         Maharashtra
2569
destination_place         Bilaspur_HB
745
corridor                 Bangalore_Nelmngla_H (Karnataka) <---> Bengaluru...
151
state_corridor           Karnataka--Bengaluru <---> Karnataka--Bengaluru
1333
city_corridor            Bengaluru--Nelmngla_H <---> Bengaluru--KGAirpr...
151

trip_df = trip_agg_df.copy()

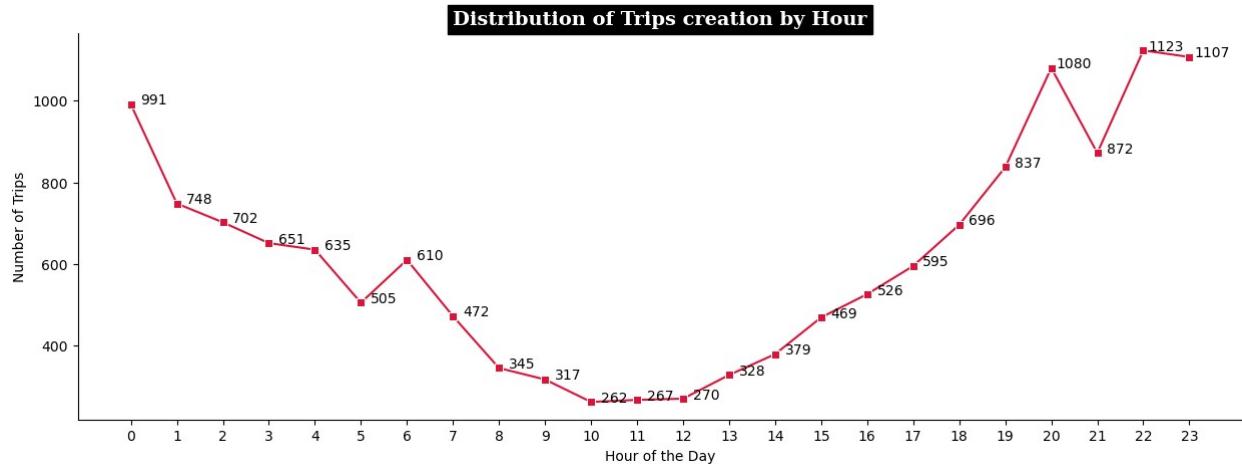
trip_creation_by_hour = trip_df.groupby(by='trip_creation_hour')[['trip_uuid']].count().reset_index()

plt.figure(figsize=(15,5))
sns.lineplot(data=trip_creation_by_hour, x='trip_creation_hour', y='trip_uuid', marker='s', color='crimson')
plt.xticks(np.arange(0, 24))

for i, count in enumerate(trip_creation_by_hour['trip_uuid']):
    plt.text(trip_creation_by_hour['trip_creation_hour'][i]+0.5, count, count, ha='center')

plt.title('Distribution of Trips creation by Hour', fontsize=14, fontfamily='serif', fontweight='bold', backgroundcolor='k', color='w')
plt.xlabel('Hour of the Day')
plt.ylabel('Number of Trips')
sns.despine()
plt.show()

```



```
trip_df.sample()

    trip_uuid      data route_type
od_start_time \
7917  trip-153765583943264913  training     Carting 2018-09-22
22:37:19.432896

                    od_end_time  od_time_diff_hour
trip_creation_time \
7917  2018-09-22 23:19:42.965506           0.706537 2018-09-22
22:37:19.432896

    trip_creation_month  trip_creation_year  trip_creation_day \
7917                  9                      2018                   22

    trip_creation_hour  trip_creation_weekday  trip_creation_week \
7917                  22                         5                     38

    start_scan_to_end_scan  actual_distance_to_destination
actual_time \
7917                      42.0                      12.338054
14.0

    osrm_time  osrm_distance  segment_actual_time  segment_osrm_time
\
7917          9.0          12.3592            13.0             9.0

    segment_osrm_distance  segment_actual_time_sum
segment_osrm_time_sum \
7917          12.359099            13.0
9.0

    segment_osrm_distance_sum  source_name
source_city \
7917          12.359099  Sonipat_AmzonDev_V (Haryana)
```

```
Sonipat

    source_state source_place           destination_name
destination_city \
7917      Haryana   AmzonDev_V  Sonipat_Kundli_P (Haryana)
Sonipat

    destination_state destination_place \
7917            Haryana          Kundli_P

                                         corridor \
7917  Sonipat_AmzonDev_V (Haryana) <---> Sonipat_Kun...
                                         state_corridor \
7917  Haryana--Sonipat <---> Haryana--Sonipat

                                         city_corridor
7917  Sonipat--AmzonDev_V <---> Sonipat--Kundli_P

trip_df.trip_creation_year.value_counts()

trip_creation_year
2018    14787
Name: count, dtype: int64

trip_df.trip_creation_month.value_counts()

trip_creation_month
9       13011
10      1776
Name: count, dtype: int64

trip_df['trip_creation_month'].value_counts(normalize = True) * 100

trip_creation_month
9      87.98945
10     12.01055
Name: proportion, dtype: float64

trip_df.trip_creation_week.value_counts()

trip_creation_week
38      5001
39      4402
37      3608
40      1776
Name: count, dtype: Int64

trip_df.trip_creation_weekday.value_counts(ascending=True)

trip_creation_weekday
6      1753
```

```
0    1980
1    2035
4    2057
3    2103
5    2128
2    2731
Name: count, dtype: int64

trip_df['trip_creation_day_week'] =
trip_df['trip_creation_time'].dt.day_name()

trip_df.trip_creation_day.value_counts()

trip_creation_day
18    791
15    783
13    750
12    747
21    740
22    740
17    722
14    712
20    703
25    695
26    683
19    674
24    658
27    650
23    631
3     627
16    616
28    605
29    605
1     600
2     549
30    506
Name: count, dtype: int64

trip_df.sample()

          trip_uuid      data route_type
od_start_time \
8403  trip-153772987770593762  training        FTL 2018-09-24
00:14:22.226774

          od_end_time  od_time_diff_hour
trip_creation_time \
8403 2018-09-24 02:42:00.976996           3.847563 2018-09-23
19:11:17.706293

  trip_creation_month  trip_creation_year  trip_creation_day \
```

```

8403 9 2018 23
    trip_creation_hour trip_creation_weekday trip_creation_week \
8403 19 6 38
        start_scan_to_end_scan actual_distance_to_destination
actual_time \
8403 230.0 69.34938
130.0
    osrm_time osrm_distance segment_actual_time segment_osrm_time \
\
8403 82.0 79.446396 129.0 86.0
        segment_osrm_distance segment_actual_time_sum
segment_osrm_time_sum \
8403 83.658005 129.0
86.0
        segment_osrm_distance_sum source_name \
8403 83.658005 Pattukotai_anthniyr_D (Tamil Nadu)
        source_city source_state source_place
destination_name \
8403 Pattukotai Tamil Nadu anthniyr_D Peravurani_SH71_D (Tamil Nadu)
        destination_city destination_state destination_place \
8403 Peravurani Tamil Nadu SH71_D
        corridor \
8403 Pattukotai_anthniyr_D (Tamil Nadu) <---> Perav...
        state_corridor \
8403 Tamil Nadu--Pattukotai <---> Tamil Nadu--Perav...
        city_corridor
trip_creation_day_week \
8403 Pattukotai--anthniyr_D <---> Peravurani--SH71_D
Sunday
        trip_creation_dayofdate
8403 23
plt.figure(figsize=(15,6))

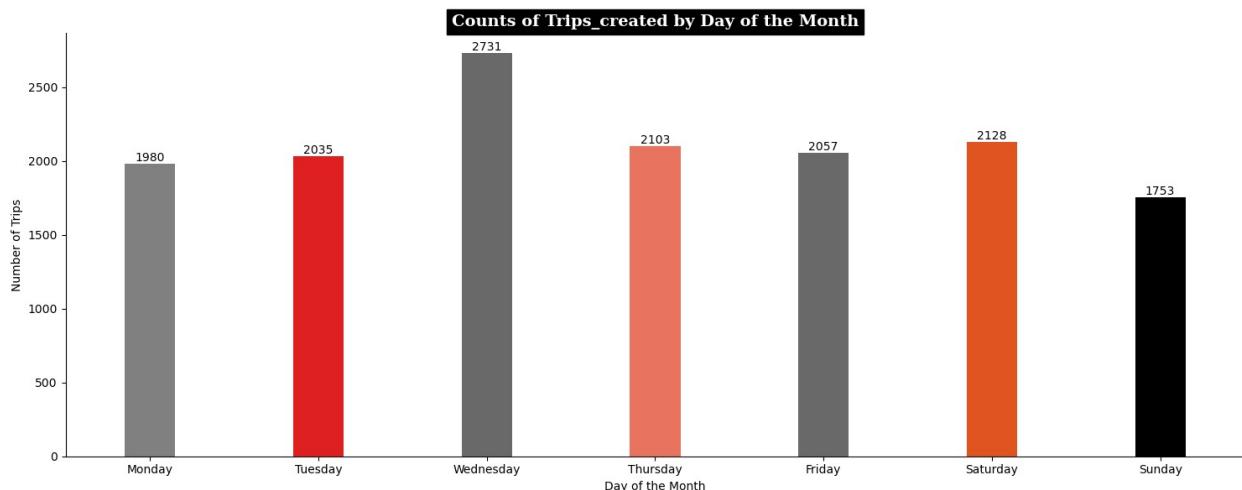
weekday_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday',
'Friday', 'Saturday', 'Sunday']
day_counts =
trip_df['trip_creation_day_week'].value_counts().reindex(weekday_order)

```

```

)
sns.barplot(x=day_counts.index, y=day_counts.values,
palette=cp, width=0.3)
for i, count in enumerate(day_counts.values):
    plt.text(i, count, str(count), ha='center', va='bottom')
plt.title('Counts of Trips_created by Day of the Month', fontsize=14, fontfamily='serif', fontweight='bold', backgroundcolor='k', color='w')
plt.xlabel('Day of the Month')
plt.ylabel('Number of Trips')
plt.tight_layout()
sns.despine()
plt.show()

```



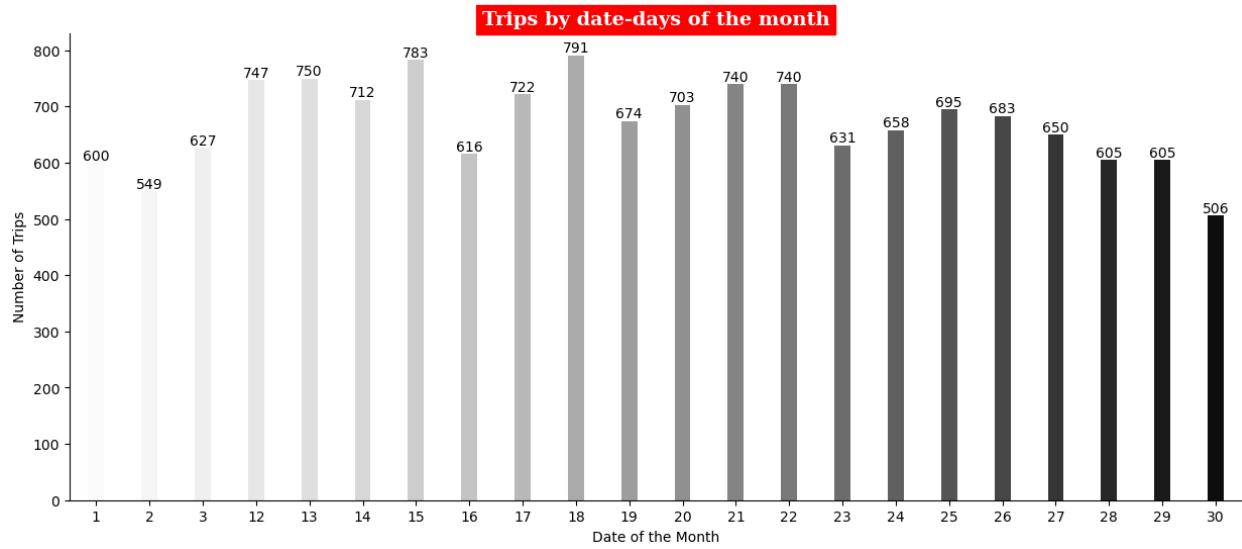
```

trip_df['trip_creation_dayofdate'] =
trip_df['trip_creation_time'].dt.day

trips_by_dateday = trip_df.groupby(by = 'trip_creation_dayofdate')[['trip_uuid']].count().to_frame().reset_index()

plt.figure(figsize = (15, 6))
sns.barplot(data =trip_df,x =
trips_by_dateday['trip_creation_dayofdate'],y =
trips_by_dateday['trip_uuid'], palette='Greys',width=0.3)
for i, count in enumerate(trips_by_dateday['trip_uuid']):
    plt.text(i, count, str(count), ha='center', va='bottom')
plt.title('Trips by date-days of the month', fontsize=14, fontfamily='serif', fontweight='bold', backgroundcolor='r', color='w')
plt.xlabel('Date of the Month')
plt.ylabel('Number of Trips')
sns.despine()
plt.show()

```



Outlier treatment

numerical_columns

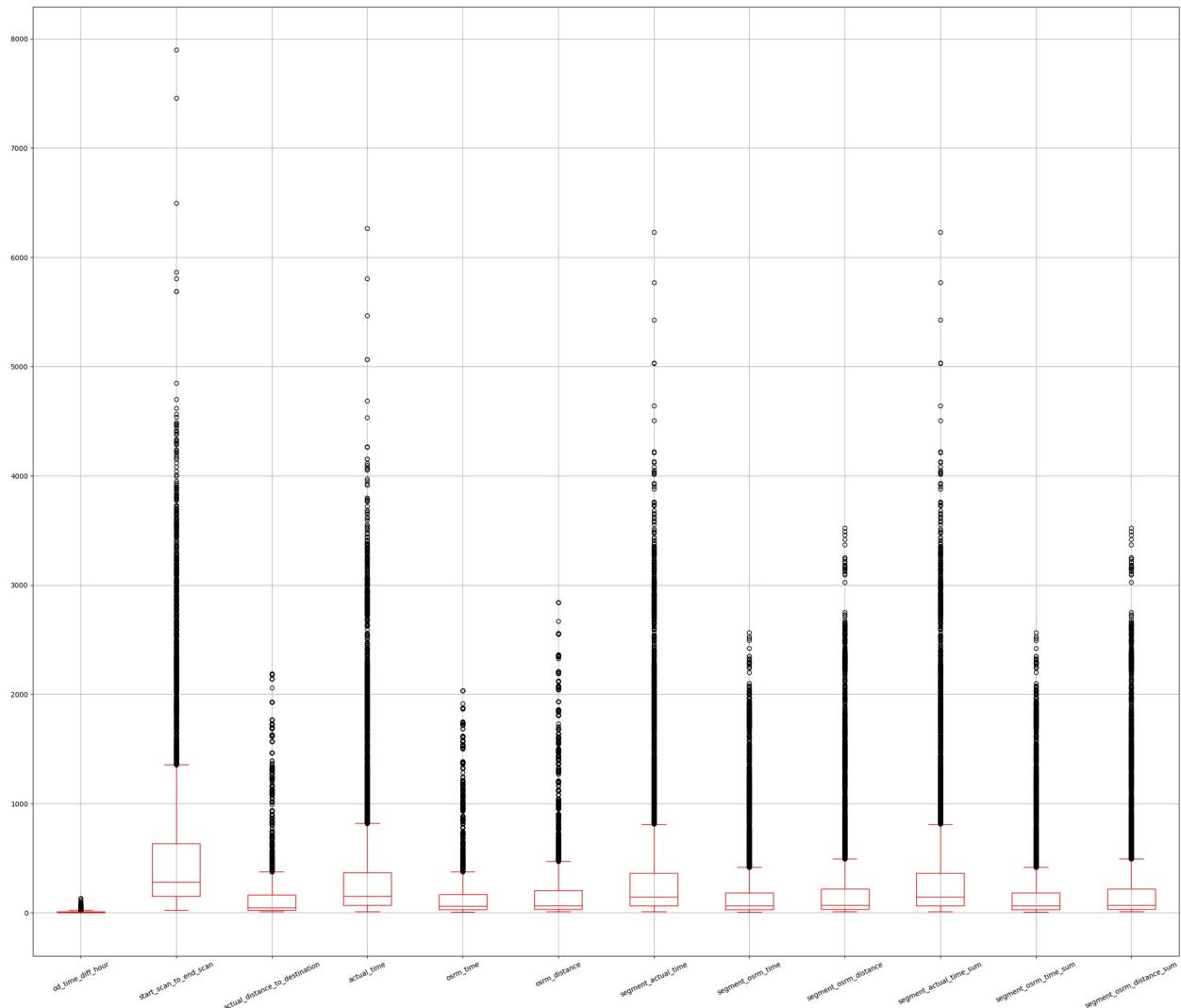
	od_time_diff_hour	start_scan_to_end_scan	\
0	37.668497	2259.0	
1	3.026865	180.0	
2	65.572709	3933.0	
3	1.674916	100.0	
4	11.972484	717.0	
...	
14782	4.300482	257.0	
14783	1.009842	60.0	
14784	7.035331	421.0	
14785	5.808548	347.0	
14786	5.906793	353.0	
osrm_distance	actual_distance_to_destination	actual_time	osrm_time
0	824.732849	1562.0	717.0
991.352295			
1	73.186905	143.0	68.0
85.111000			
2	1927.404297	3347.0	1740.0
2354.066650			
3	17.175274	59.0	15.0
19.680000			
4	127.448502	341.0	117.0
146.791794			
...
...
14782	57.762333	83.0	62.0
73.462997			

14783	15.513784	21.0	12.0
16.088200			
14784	38.684837	282.0	48.0
58.903702			
14785	134.723831	264.0	179.0
171.110306			
14786	66.081528	275.0	68.0
80.578705			
segment_actual_time segment_osrm_time			
segment_osrm_distance \			
0	1548.0	1008.0	1320.473267
1	141.0	65.0	84.189400
2	3308.0	1941.0	2545.267822
3	59.0	16.0	19.876600
4	340.0	115.0	146.791901
...
14782	82.0	62.0	64.855103
14783	21.0	11.0	16.088299
14784	281.0	88.0	104.886597
14785	258.0	221.0	223.532394
14786	274.0	67.0	80.578705
segment_actual_time_sum segment_osrm_time_sum \			
0	1548.0	1008.0	
1	141.0	65.0	
2	3308.0	1941.0	
3	59.0	16.0	
4	340.0	115.0	
...	
14782	82.0	62.0	
14783	21.0	11.0	
14784	281.0	88.0	
14785	258.0	221.0	
14786	274.0	67.0	
segment_osrm_distance_sum			
0	1320.473267		
1	84.189400		
2	2545.267822		

```
3          19.876600
4          146.791901
...
14782      64.855103
14783      16.088299
14784      104.886597
14785      223.532394
14786      80.578705
```

```
[14787 rows x 12 columns]
```

```
plt.figure(figsize=(30, 25))
numerical_columns.boxplot(rot=25, figsize=(35,20), color = 'r')
plt.grid('off')
plt.show()
```



```
numerical_columns.columns
```

```

Index(['od_time_diff_hour', 'start_scan_to_end_scan',
       'actual_distance_to_destination', 'actual_time', 'osrm_time',
       'osrm_distance', 'segment_actual_time', 'segment_osrm_time',
       'segment_osrm_distance', 'segment_actual_time_sum',
       'segment_osrm_time_sum', 'segment_osrm_distance_sum'],
      dtype='object')

num_cols = numerical_columns.columns.tolist()
num_cols

['od_time_diff_hour',
 'start_scan_to_end_scan',
 'actual_distance_to_destination',
 'actual_time',
 'osrm_time',
 'osrm_distance',
 'segment_actual_time',
 'segment_osrm_time',
 'segment_osrm_distance',
 'segment_actual_time_sum',
 'segment_osrm_time_sum',
 'segment_osrm_distance_sum']

# obtain the first quartile
Q1 = numerical_columns.quantile(0.25)

# obtain the third quartile
Q3 = numerical_columns.quantile(0.75)

# obtain the IQR
IQR = Q3 - Q1

# print the IQR
print(IQR)

od_time_diff_hour           8.063987
start_scan_to_end_scan     483.000000
actual_distance_to_destination 140.814157
actual_time                 300.000000
osrm_time                   139.000000
osrm_distance                175.887303
segment_actual_time         298.000000
segment_osrm_time            154.000000
segment_osrm_distance        183.981758
segment_actual_time_sum     298.000000
segment_osrm_time_sum       154.000000
segment_osrm_distance_sum   183.981758
dtype: float64

for i,col in enumerate(numerical_columns):
    plt.figure(figsize=(15,4))

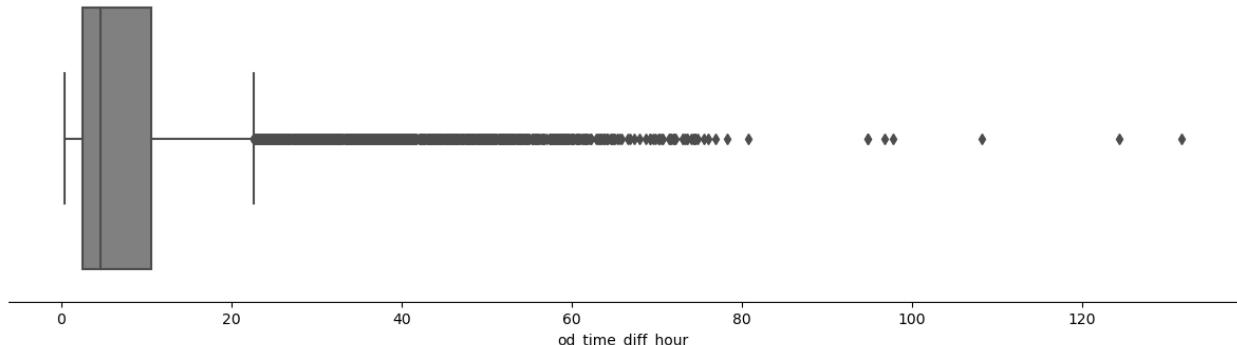
```

```

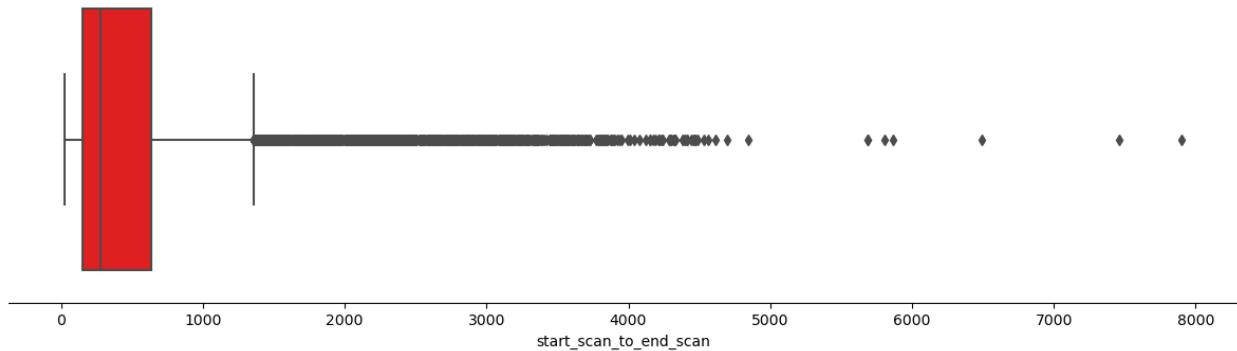
sns.boxplot(x=col, data=numerical_columns,color=cp[i])
sns.despine(left=True)
plt.yticks([])
plt.title(f'Boxplot of {col}',fontfamily='serif',fontweight='bold',fontsize=12,backgroundcolor=cp[i],color='w')
plt.show()

```

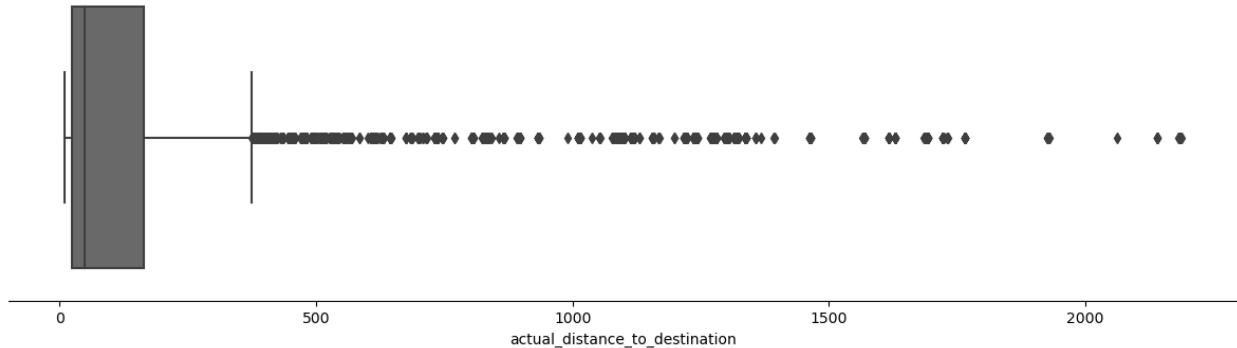
Boxplot of od_time_diff_hour



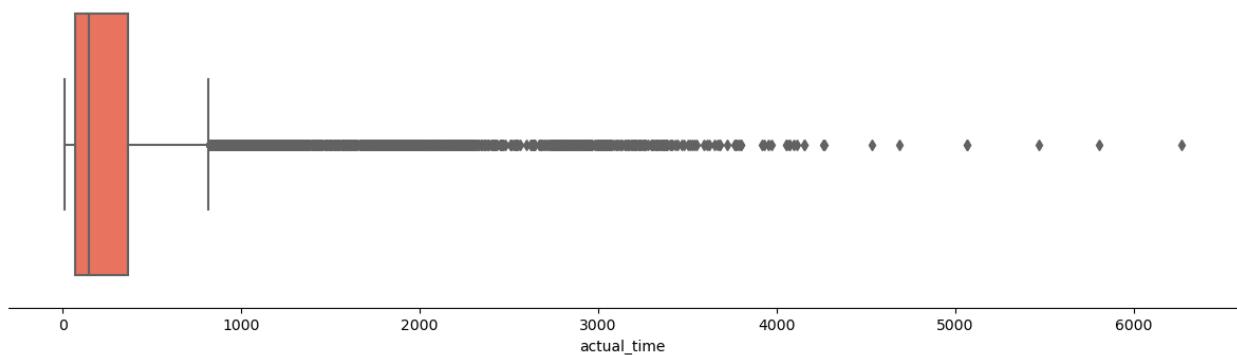
Boxplot of start_scan_to_end_scan



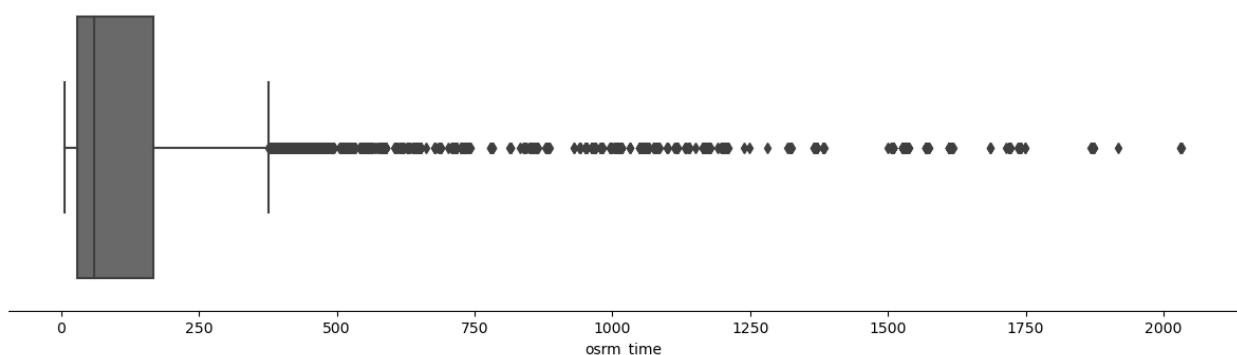
Boxplot of actual_distance_to_destination



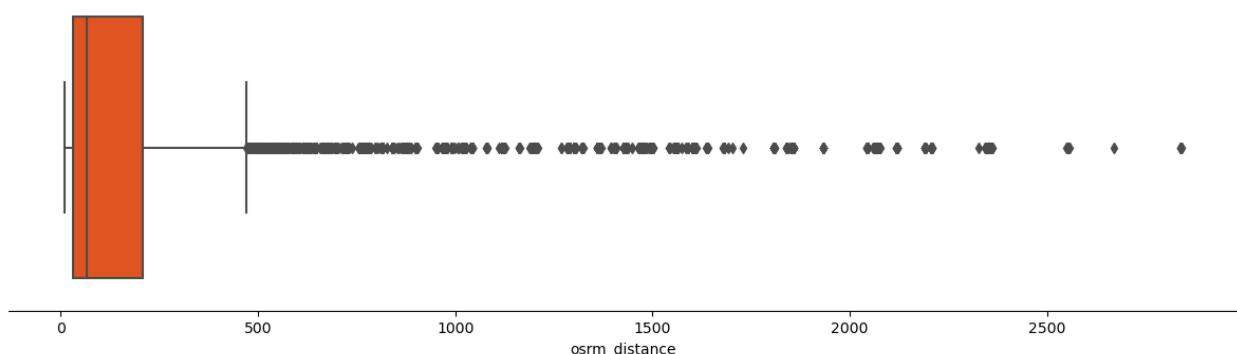
Boxplot of actual_time



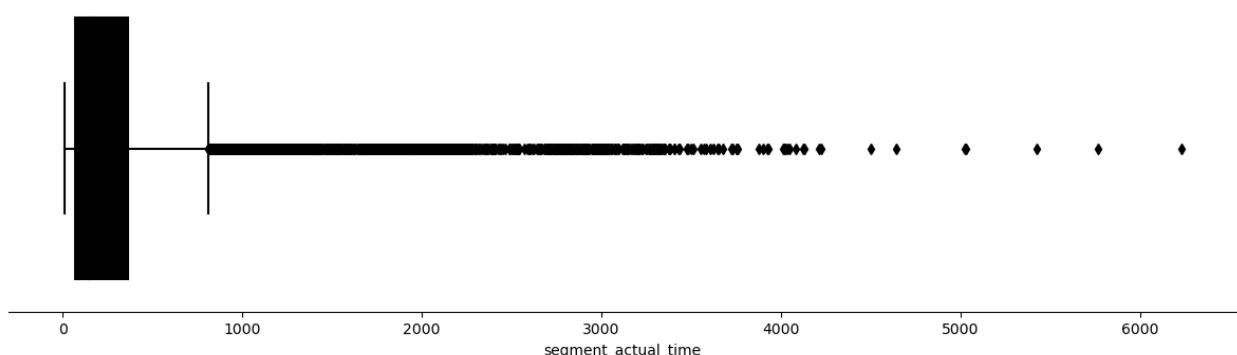
Boxplot of osrm_time



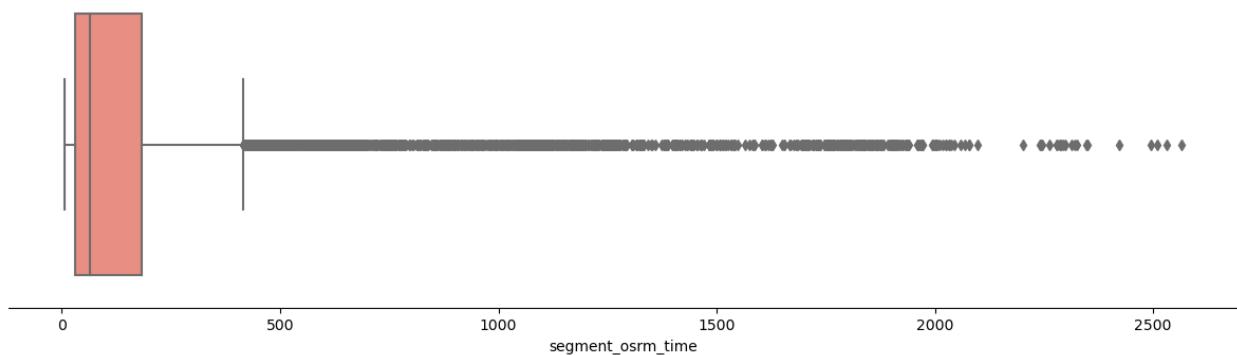
Boxplot of osrm_distance



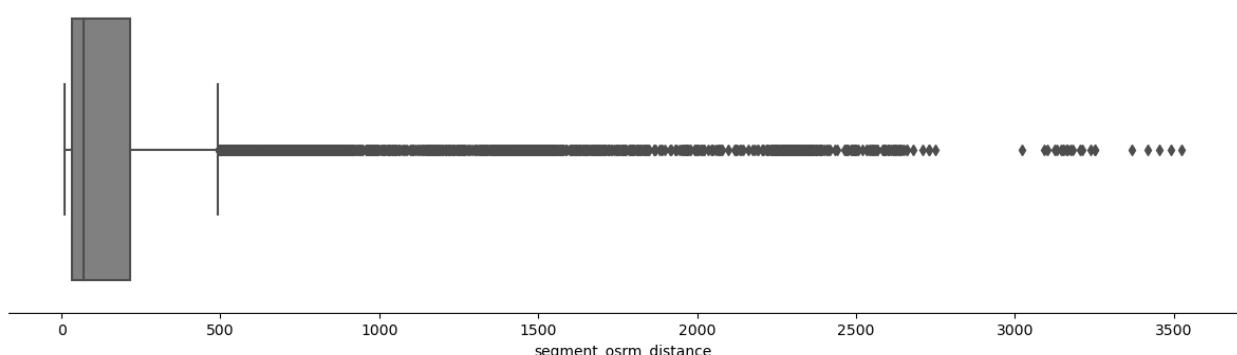
Boxplot of segment_actual_time



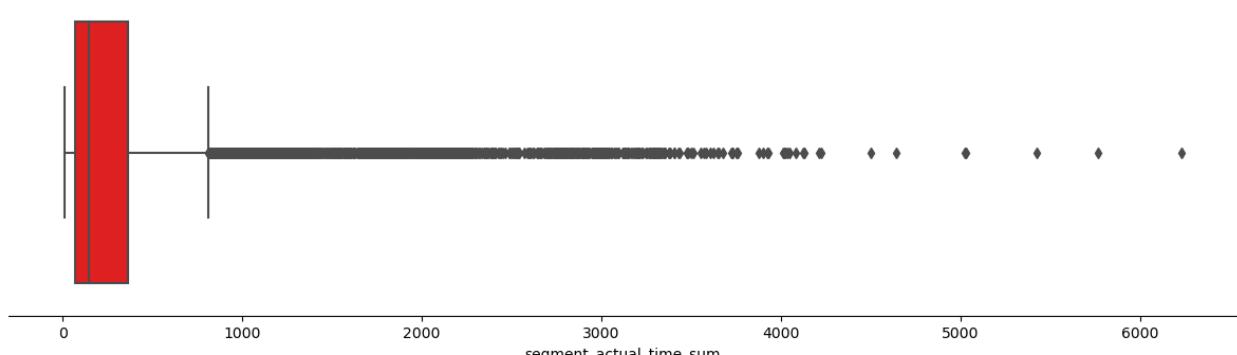
Boxplot of segment_osrm_time



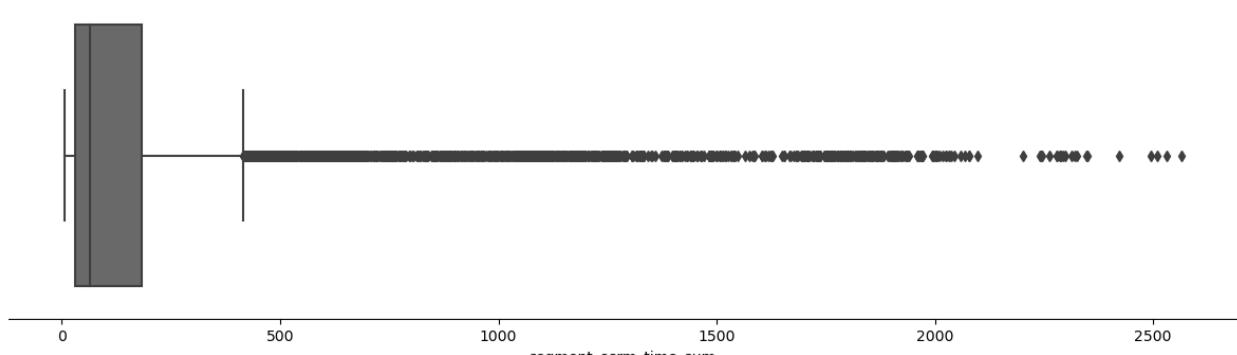
Boxplot of segment_osrm_distance



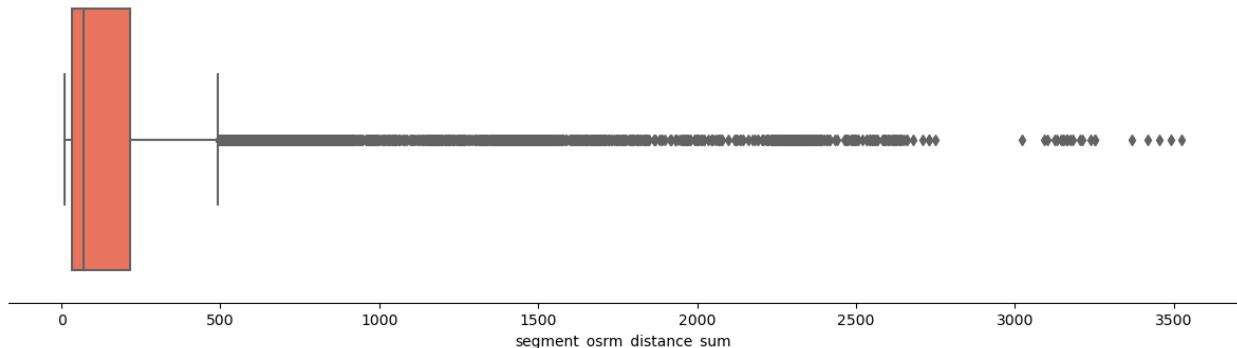
Boxplot of segment_actual_time_sum



Boxplot of segment_osrm_time_sum



Boxplot of segment_osrm_distance_sum



Outlier Removal

```
for i, col in enumerate(numerical_columns):

    data = trip_df[col]
    display(data.to_frame())

    Q1 = np.percentile(data, 25)
    Q3 = np.percentile(data, 75)
    IQR = Q3 - Q1

    lower_bound = Q1 - (1.5 * IQR)
    upper_bound = Q3 + (1.5 * IQR)

    clipped_data = np.clip(data, lower_bound, upper_bound)
    print(f'Clipped data of {col}')
    display(clipped_data.to_frame())
    print()

    # Plot boxplot of the clipped data
    plt.figure(figsize=(15, 4))
    plt.subplot(121)
    sns.boxplot(x=clipped_data, color=cp[i])
    sns.despine(left=True)
    plt.yticks([])
    plt.title(f'Boxplot of clipped {col}', fontfamily='serif',
              fontweight='bold', fontsize=12, backgroundcolor=cp[i], color='w')

    filtered_data = data.loc[(data >= lower_bound) | (data <=
upper_bound)]
    print(f'Filtered data of {col}')
    display(filtered_data.to_frame())
    print()

    plt.subplot(122)
    sns.boxplot(x=filtered_data, color=cp[i])
```

```
sns.despine(left=True)
plt.yticks([])
plt.title(f'Boxplot of filtered {col}', fontfamily='serif',
fontweight='bold', fontsize=12, backgroundcolor=cp[i], color='w')

plt.show()

od_time_diff_hour
0           37.668497
1            3.026865
2           65.572709
3            1.674916
4           11.972484
...
14782        4.300482
14783        1.009842
14784        7.035331
14785        5.808548
14786        5.906793

[14787 rows x 1 columns]

Clipped data of od_time_diff_hour

od_time_diff_hour
0           22.654942
1            3.026865
2           22.654942
3            1.674916
4           11.972484
...
14782        4.300482
14783        1.009842
14784        7.035331
14785        5.808548
14786        5.906793

[14787 rows x 1 columns]

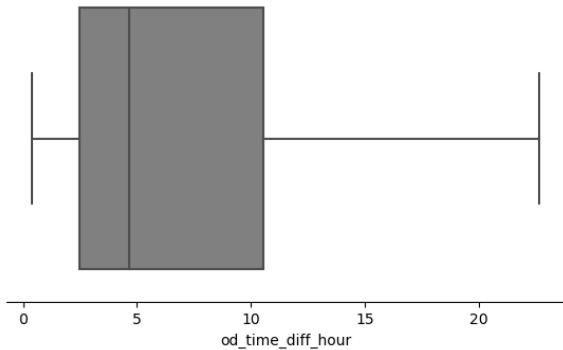
Filtered data of od_time_diff_hour

od_time_diff_hour
0           37.668497
1            3.026865
2           65.572709
3            1.674916
4           11.972484
...
14782        4.300482
14783        1.009842
```

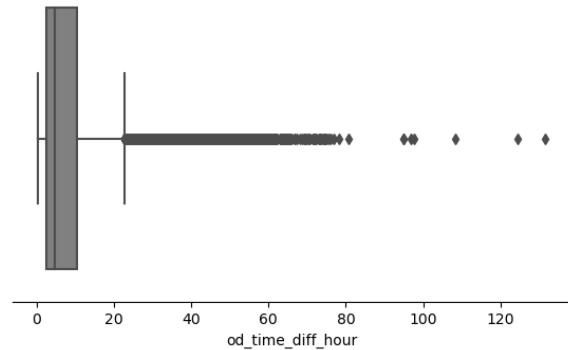
```
14784      7.035331
14785      5.808548
14786      5.906793
```

```
[14787 rows x 1 columns]
```

Boxplot of clipped od_time_diff_hour



Boxplot of filtered od_time_diff_hour



```
start_scan_to_end_scan
0                  2259.0
1                  180.0
2                  3933.0
3                  100.0
4                  717.0
...
14782              257.0
14783              60.0
14784              421.0
14785              347.0
14786              353.0
```

```
[14787 rows x 1 columns]
```

Clipped data of start_scan_to_end_scan

```
start_scan_to_end_scan
0                  1356.5
1                  180.0
2                  1356.5
3                  100.0
4                  717.0
...
14782              257.0
14783              60.0
14784              421.0
14785              347.0
14786              353.0
```

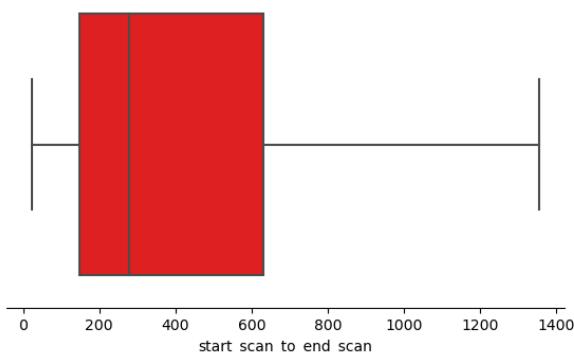
```
[14787 rows x 1 columns]
```

Filtered data of start_scan_to_end_scan

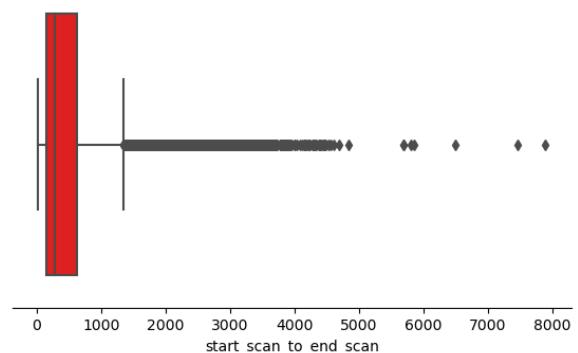
```
    start_scan_to_end_scan
0                  2259.0
1                  180.0
2                 3933.0
3                  100.0
4                  717.0
...
14782                ...
14783                ...
14784                ...
14785                ...
14786                ...
```

```
[14787 rows x 1 columns]
```

Boxplot of clipped start_scan_to_end_scan



Boxplot of filtered start_scan_to_end_scan



```
actual_distance_to_destination
0                      824.732849
1                      73.186905
2                     1927.404297
3                      17.175274
4                     127.448502
...
14782                ...
14783                ...
14784                ...
14785                ...
14786                ...
```

```
[14787 rows x 1 columns]
```

```
Clipped data of actual_distance_to_destination
```

```
    actual_distance_to_destination
0                  374.812490
1                  73.186905
2                  374.812490
3                  17.175274
4                 127.448502
...
14782             ...
14783             15.513784
14784             38.684837
14785             134.723831
14786             66.081528
```

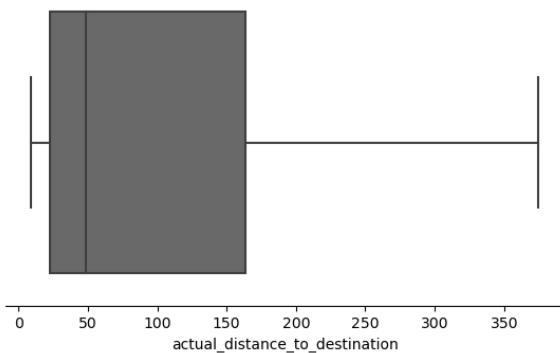
```
[14787 rows x 1 columns]
```

```
Filtered data of actual_distance_to_destination
```

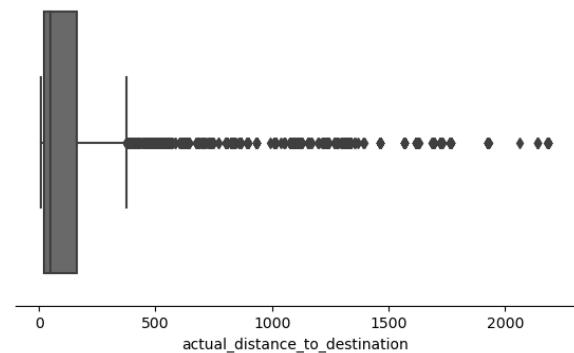
```
    actual_distance_to_destination
0                  824.732849
1                  73.186905
2                 1927.404297
3                  17.175274
4                 127.448502
...
14782             ...
14783             15.513784
14784             38.684837
14785             134.723831
14786             66.081528
```

```
[14787 rows x 1 columns]
```

Boxplot of clipped actual_distance_to_destination



Boxplot of filtered actual_distance_to_destination



```
    actual_time
0          1562.0
1          143.0
2         3347.0
3           59.0
4          341.0
...
14782      ...
14783      21.0
14784      282.0
14785      264.0
14786      275.0
```

[14787 rows x 1 columns]

Clipped data of actual_time

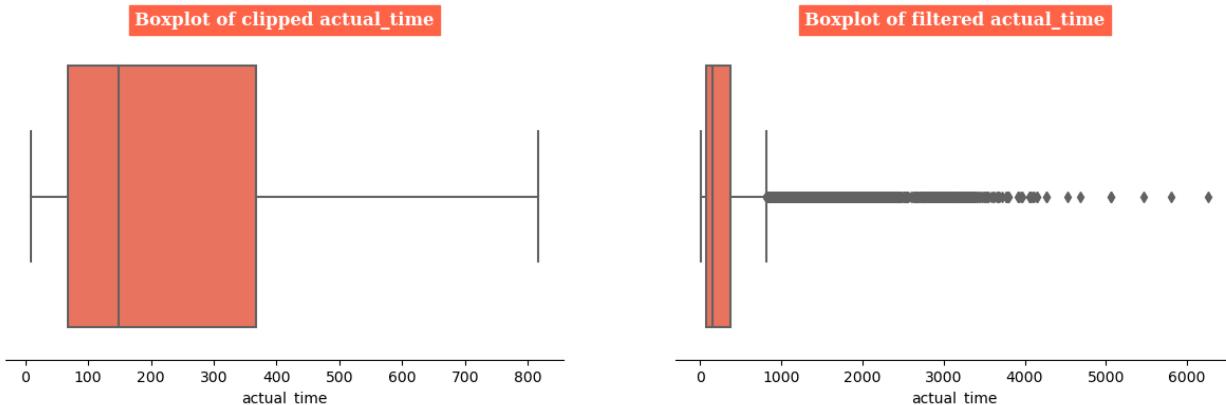
```
    actual_time
0          817.0
1          143.0
2          817.0
3           59.0
4          341.0
...
14782      ...
14783      21.0
14784      282.0
14785      264.0
14786      275.0
```

[14787 rows x 1 columns]

Filtered data of actual_time

```
    actual_time
0          1562.0
1          143.0
2         3347.0
3           59.0
4          341.0
...
14782      ...
14783      21.0
14784      282.0
14785      264.0
14786      275.0
```

[14787 rows x 1 columns]



```
osrm_time
0      717.0
1       68.0
2     1740.0
3      15.0
4     117.0
...
14782    62.0
14783    12.0
14784    48.0
14785   179.0
14786    68.0

[14787 rows x 1 columns]
```

Clipped data of osrm_time

```
osrm_time
0      376.5
1       68.0
2     376.5
3      15.0
4     117.0
...
14782    62.0
14783    12.0
14784    48.0
14785   179.0
14786    68.0
```

[14787 rows x 1 columns]

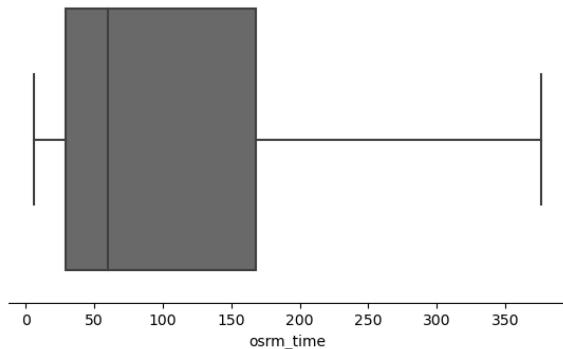
Filtered data of osrm_time

```
osrm_time
0      717.0
1       68.0
```

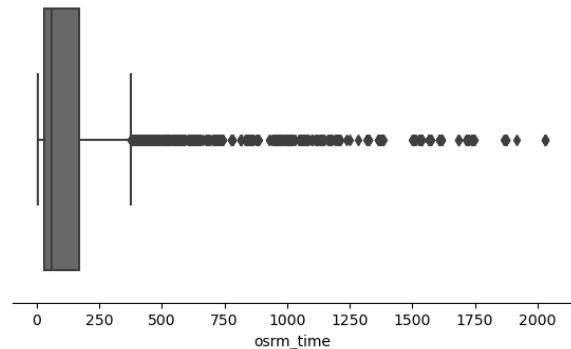
```
2          1740.0
3          15.0
4         117.0
...
14782      62.0
14783      12.0
14784      48.0
14785     179.0
14786      68.0
```

[14787 rows x 1 columns]

Boxplot of clipped osrm_time



Boxplot of filtered osrm_time



```
osrm_distance
0          991.352295
1          85.111000
2         2354.066650
3          19.680000
4         146.791794
...
14782      73.462997
14783      16.088200
14784      58.903702
14785     171.110306
14786      80.578705
```

[14787 rows x 1 columns]

Clipped data of osrm_distance

```
osrm_distance
0          470.475158
1          85.111000
2          470.475158
3          19.680000
4         146.791794
```

```
...      ...
14782    73.462997
14783    16.088200
14784    58.903702
14785    171.110306
14786    80.578705
```

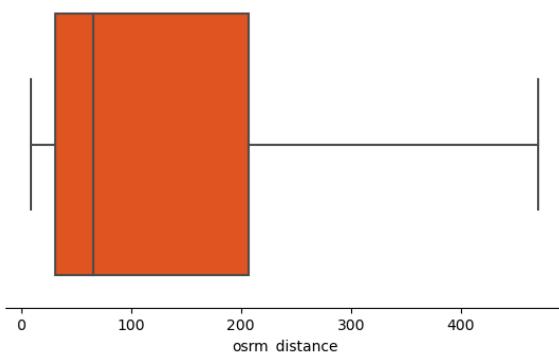
[14787 rows x 1 columns]

Filtered data of osrm_distance

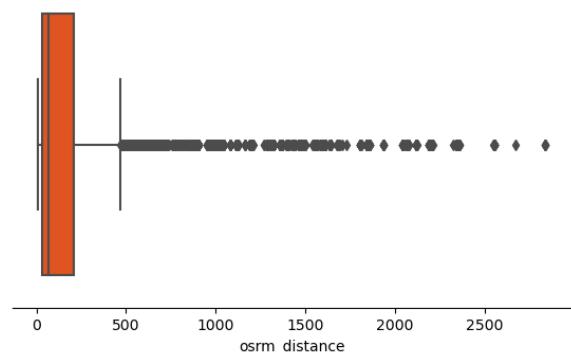
```
osrm_distance
0        991.352295
1        85.111000
2       2354.066650
3        19.680000
4       146.791794
...
14782    73.462997
14783    16.088200
14784    58.903702
14785    171.110306
14786    80.578705
```

[14787 rows x 1 columns]

Boxplot of clipped osrm_distance



Boxplot of filtered osrm_distance



```
segment_actual_time
0            1548.0
1            141.0
2            3308.0
3             59.0
4            340.0
...
14782        82.0
```

```
14783          21.0
14784          281.0
14785          258.0
14786          274.0
```

```
[14787 rows x 1 columns]
```

```
Clipped data of segment_actual_time
```

```
    segment_actual_time
0                  811.0
1                  141.0
2                  811.0
3                  59.0
4                  340.0
...
14782                 ...
14783                 ...
14784                 ...
14785                 ...
14786                 ...
```

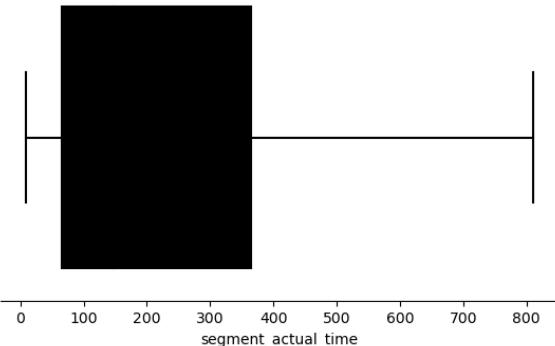
```
[14787 rows x 1 columns]
```

```
Filtered data of segment_actual_time
```

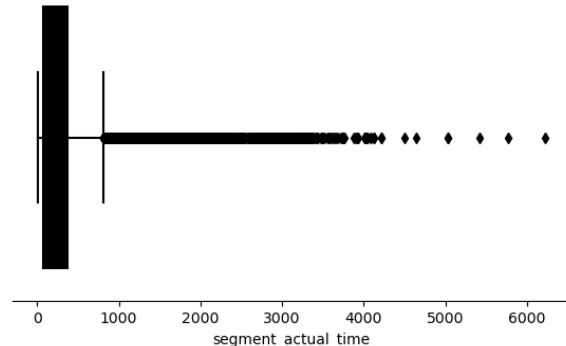
```
    segment_actual_time
0                  1548.0
1                  141.0
2                  3308.0
3                  59.0
4                  340.0
...
14782                 ...
14783                 ...
14784                 ...
14785                 ...
14786                 ...
```

```
[14787 rows x 1 columns]
```

Boxplot of clipped segment_actual_time



Boxplot of filtered segment_actual_time



```
segment_osrm_time
0           1008.0
1             65.0
2           1941.0
3             16.0
4           115.0
...
14782         ...
14783         62.0
14784         11.0
14785         88.0
14786         221.0
14786         67.0
```

[14787 rows x 1 columns]

Clipped data of segment_osrm_time

```
segment_osrm_time
0           415.0
1             65.0
2           415.0
3             16.0
4           115.0
...
14782         ...
14783         62.0
14784         11.0
14785         88.0
14786         221.0
14786         67.0
```

[14787 rows x 1 columns]

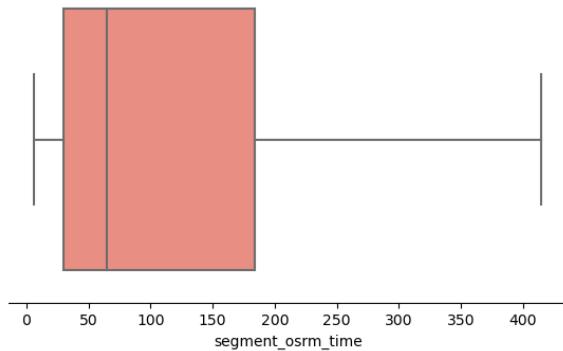
Filtered data of segment_osrm_time

```
segment_osrm_time
0           1008.0
1             65.0
```

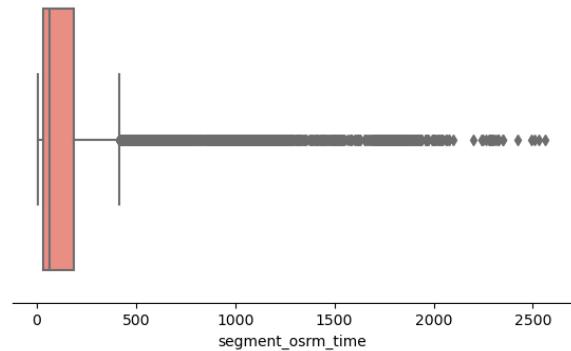
```
2           1941.0
3           16.0
4          115.0
...
14782       62.0
14783       11.0
14784       88.0
14785      221.0
14786       67.0
```

[14787 rows x 1 columns]

Boxplot of clipped segment_osrm_time



Boxplot of filtered segment_osrm_time



```
segment_osrm_distance
0           1320.473267
1           84.189400
2          2545.267822
3          19.876600
4          146.791901
...
14782       64.855103
14783       16.088299
14784       104.886597
14785      223.532394
14786       80.578705
```

[14787 rows x 1 columns]

Clipped data of segment_osrm_distance

```
segment_osrm_distance
0           492.533245
1           84.189400
2           492.533245
3           19.876600
4          146.791901
```

```
...  
14782           64.855103  
14783           16.088299  
14784          104.886597  
14785         223.532394  
14786          80.578705
```

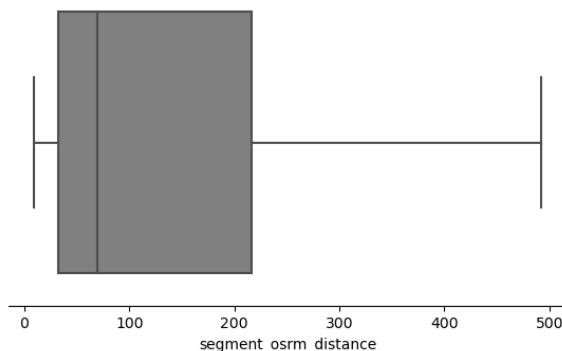
```
[14787 rows x 1 columns]
```

Filtered data of segment_osrm_distance

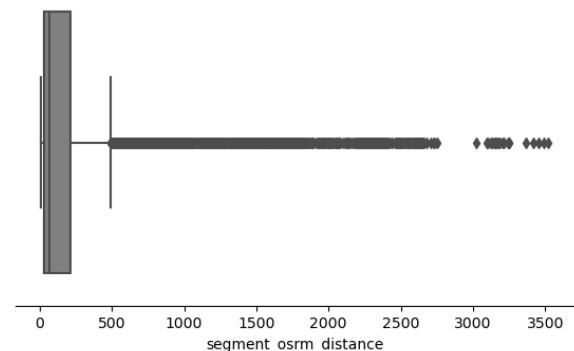
```
segment_osrm_distance  
0           1320.473267  
1           84.189400  
2          2545.267822  
3          19.876600  
4          146.791901  
...  
14782           64.855103  
14783           16.088299  
14784          104.886597  
14785         223.532394  
14786          80.578705
```

```
[14787 rows x 1 columns]
```

Boxplot of clipped segment_osrm_distance



Boxplot of filtered segment_osrm_distance



```
segment_actual_time_sum  
0           1548.0  
1           141.0  
2          3308.0  
3            59.0  
4           340.0  
...  
14782           82.0
```

```
14783          21.0
14784          281.0
14785          258.0
14786          274.0
```

[14787 rows x 1 columns]

Clipped data of segment_actual_time_sum

```
    segment_actual_time_sum
0                  811.0
1                  141.0
2                  811.0
3                  59.0
4                  340.0
...
14782             82.0
14783             21.0
14784             281.0
14785             258.0
14786             274.0
```

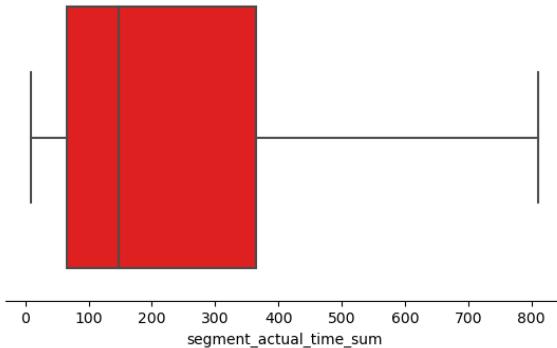
[14787 rows x 1 columns]

Filtered data of segment_actual_time_sum

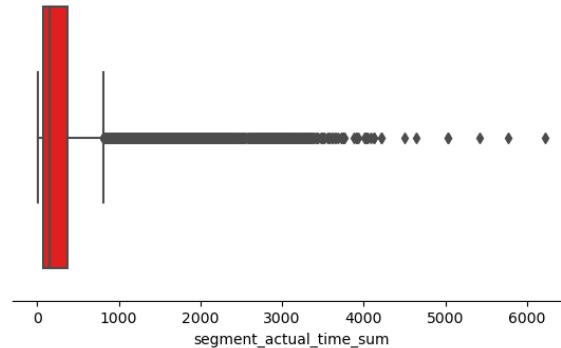
```
    segment_actual_time_sum
0                  1548.0
1                  141.0
2                 3308.0
3                  59.0
4                  340.0
...
14782             82.0
14783             21.0
14784             281.0
14785             258.0
14786             274.0
```

[14787 rows x 1 columns]

Boxplot of clipped segment_actual_time_sum



Boxplot of filtered segment_actual_time_sum



```
segment_osrm_time_sum
0 1008.0
1 65.0
2 1941.0
3 16.0
4 115.0
...
14782 62.0
14783 11.0
14784 88.0
14785 221.0
14786 67.0
```

[14787 rows x 1 columns]

Clipped data of segment_osrm_time_sum

```
segment_osrm_time_sum
0 415.0
1 65.0
2 415.0
3 16.0
4 115.0
...
14782 62.0
14783 11.0
14784 88.0
14785 221.0
14786 67.0
```

[14787 rows x 1 columns]

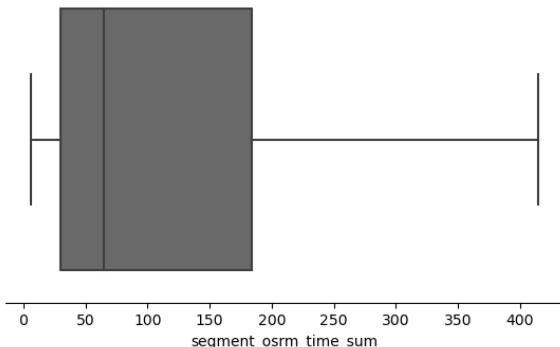
Filtered data of segment_osrm_time_sum

```
segment_osrm_time_sum
0 1008.0
1 65.0
```

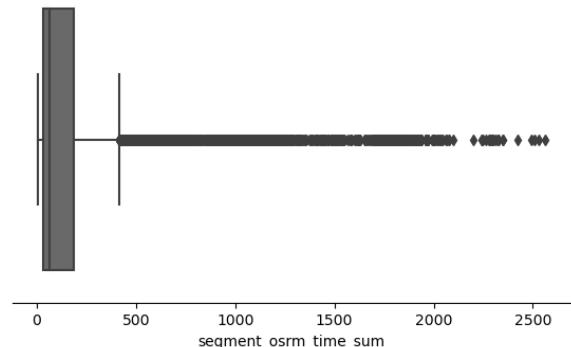
```
2           1941.0
3           16.0
4          115.0
...
14782        62.0
14783        11.0
14784        88.0
14785      221.0
14786        67.0
```

[14787 rows x 1 columns]

Boxplot of clipped segment_osrm_time_sum



Boxplot of filtered segment_osrm_time_sum



```
segment_osrm_distance_sum
0           1320.473267
1           84.189400
2          2545.267822
3          19.876600
4          146.791901
...
14782        64.855103
14783        16.088299
14784        104.886597
14785      223.532394
14786        80.578705
```

[14787 rows x 1 columns]

Clipped data of segment_osrm_distance_sum

```
segment_osrm_distance_sum
0           492.533245
1           84.189400
2           492.533245
3           19.876600
4          146.791901
```

```

...
14782           64.855103
14783          16.088299
14784          104.886597
14785         223.532394
14786          80.578705

```

[14787 rows x 1 columns]

Filtered data of segment_osrm_distance_sum

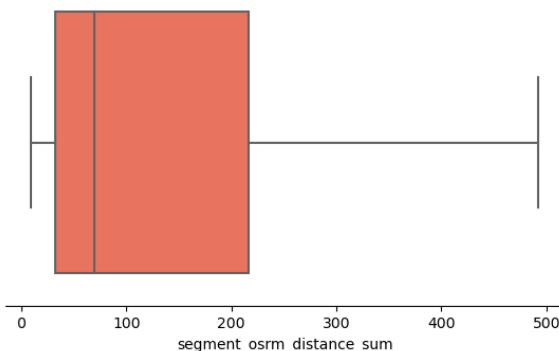
```

segment_osrm_distance_sum
0                  1320.473267
1                  84.189400
2                 2545.267822
3                 19.876600
4                 146.791901
...
14782           64.855103
14783          16.088299
14784          104.886597
14785         223.532394
14786          80.578705

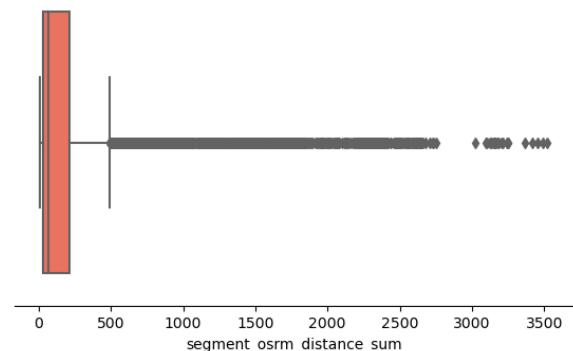
```

[14787 rows x 1 columns]

Boxplot of clipped segment_osrm_distance_sum



Boxplot of filtered segment_osrm_distance_sum



Understanding:

- Here we see that the data after removing outliers has outliers. It has to be understood that q1 and q3 dont have to be always 25th percentile and 75th percentile. ***Try changing q1 and q3 to 10th percentile to 90th percentile and plot and see...***
- Clipped data replaces the outlier values with specified values.
- Here, I have proceeded with both clipped and filtered data(with reduced outliers) for further analysis.

```

num_df = numerical_columns.copy()
num_df

      od_time_diff_hour  start_scan_to_end_scan \
0            37.668497                2259.0
1             3.026865                 180.0
2            65.572709                3933.0
3             1.674916                 100.0
4            11.972484                 717.0
...
14782          ...                   ...
14783          ...                   ...
14784          ...                   ...
14785          ...                   ...
14786          ...                   ...

      actual_distance_to_destination  actual_time  osrm_time
osrm_distance \
0                         824.732849        1562.0       717.0
991.352295
1                         73.186905        143.0        68.0
85.111000
2                         1927.404297       3347.0      1740.0
2354.066650
3                         17.175274         59.0        15.0
19.680000
4                         127.448502       341.0       117.0
146.791794
...
...
14782          ...                   ...
14783          ...                   ...
14784          ...                   ...
14785          ...                   ...
14786          ...                   ...
80.578705

      segment_actual_time  segment_osrm_time
segment_osrm_distance \
0                     1548.0           1008.0        1320.473267
1                     141.0            65.0          84.189400
2                     3308.0          1941.0        2545.267822
3                      59.0            16.0          19.876600

```

```

4           340.0          115.0        146.791901
...
14782         82.0          62.0        64.855103
14783         21.0          11.0        16.088299
14784         281.0          88.0        104.886597
14785         258.0          221.0       223.532394
14786         274.0          67.0        80.578705

      segment_actual_time_sum  segment_osrm_time_sum \
0                  1548.0            1008.0
1                  141.0             65.0
2                  3308.0            1941.0
3                  59.0              16.0
4                  340.0            115.0
...
14782         82.0          62.0
14783         21.0          11.0
14784         281.0          88.0
14785         258.0          221.0
14786         274.0          67.0

      segment_osrm_distance_sum
0                  1320.473267
1                  84.189400
2                  2545.267822
3                  19.876600
4                  146.791901
...
14782         64.855103
14783         16.088299
14784         104.886597
14785         223.532394
14786         80.578705

[14787 rows x 12 columns]

num_cols

['od_time_diff_hour',
 'start_scan_to_end_scan',
 'actual_distance_to_destination',
 'actual_time',
 'osrm_time'],

```

```

'osrm_distance',
'segment_actual_time',
'segment_osrm_time',
'segment_osrm_distance',
'segment_actual_time_sum',
'segment_osrm_time_sum',
'segment_osrm_distance_sum']

Q1 = np.percentile(num_df[num_cols], 25)
Q3 = np.percentile(num_df[num_cols], 75)
IQR = Q3 - Q1

lower_bound = Q1 - (1.5 * IQR)
upper_bound = Q3 + (1.5 * IQR)

clipped_num_df = np.clip(num_df[num_cols], lower_bound, upper_bound)
display(clipped_num_df)

filtered_num_df = num_df[num_cols][(num_df[num_cols] >= lower_bound) | (num_df[num_cols] <= upper_bound)]
display(filtered_num_df)

      od_time_diff_hour  start_scan_to_end_scan \
0            37.668497           543.285302
1             3.026865           180.000000
2            65.572709           543.285302
3             1.674916           100.000000
4            11.972484           543.285302
...               ...
14782          4.300482           257.000000
14783          1.009842           60.000000
14784          7.035331           421.000000
14785          5.808548           347.000000
14786          5.906793           353.000000

      actual_distance_to_destination  actual_time  osrm_time
osrm_distance \
0                           543.285302  543.285302  543.285302
543.285302
1                           73.186905  143.000000  68.000000
85.111000
2                           543.285302  543.285302  543.285302
543.285302
3                           17.175274  59.000000  15.000000
19.680000
4                           127.448502 341.000000 117.000000
146.791794
...               ...
14782                  57.762333  83.000000  62.000000

```

73.462997			
14783	15.513784	21.000000	12.000000
16.088200			
14784	38.684837	282.000000	48.000000
58.903702			
14785	134.723831	264.000000	179.000000
171.110306			
14786	66.081528	275.000000	68.000000
80.578705			
segment_actual_time segment_osrm_time			
segment_osrm_distance \			
0	543.285302	543.285302	543.285302
1	141.000000	65.000000	84.189400
2	543.285302	543.285302	543.285302
3	59.000000	16.000000	19.876600
4	340.000000	115.000000	146.791901
...
14782	82.000000	62.000000	64.855103
14783	21.000000	11.000000	16.088299
14784	281.000000	88.000000	104.886597
14785	258.000000	221.000000	223.532394
14786	274.000000	67.000000	80.578705
segment_actual_time_sum segment_osrm_time_sum \			
0	543.285302	543.285302	
1	141.000000	65.000000	
2	543.285302	543.285302	
3	59.000000	16.000000	
4	340.000000	115.000000	
...	
14782	82.000000	62.000000	
14783	21.000000	11.000000	
14784	281.000000	88.000000	
14785	258.000000	221.000000	
14786	274.000000	67.000000	
segment_osrm_distance_sum			
0	543.285302		
1	84.189400		

2	543.285302
3	19.876600
4	146.791901
...	...
14782	64.855103
14783	16.088299
14784	104.886597
14785	223.532394
14786	80.578705

[14787 rows x 12 columns]

	od_time_diff_hour	start_scan_to_end_scan \
0	37.668497	2259.0
1	3.026865	180.0
2	65.572709	3933.0
3	1.674916	100.0
4	11.972484	717.0
...
14782	4.300482	257.0
14783	1.009842	60.0
14784	7.035331	421.0
14785	5.808548	347.0
14786	5.906793	353.0

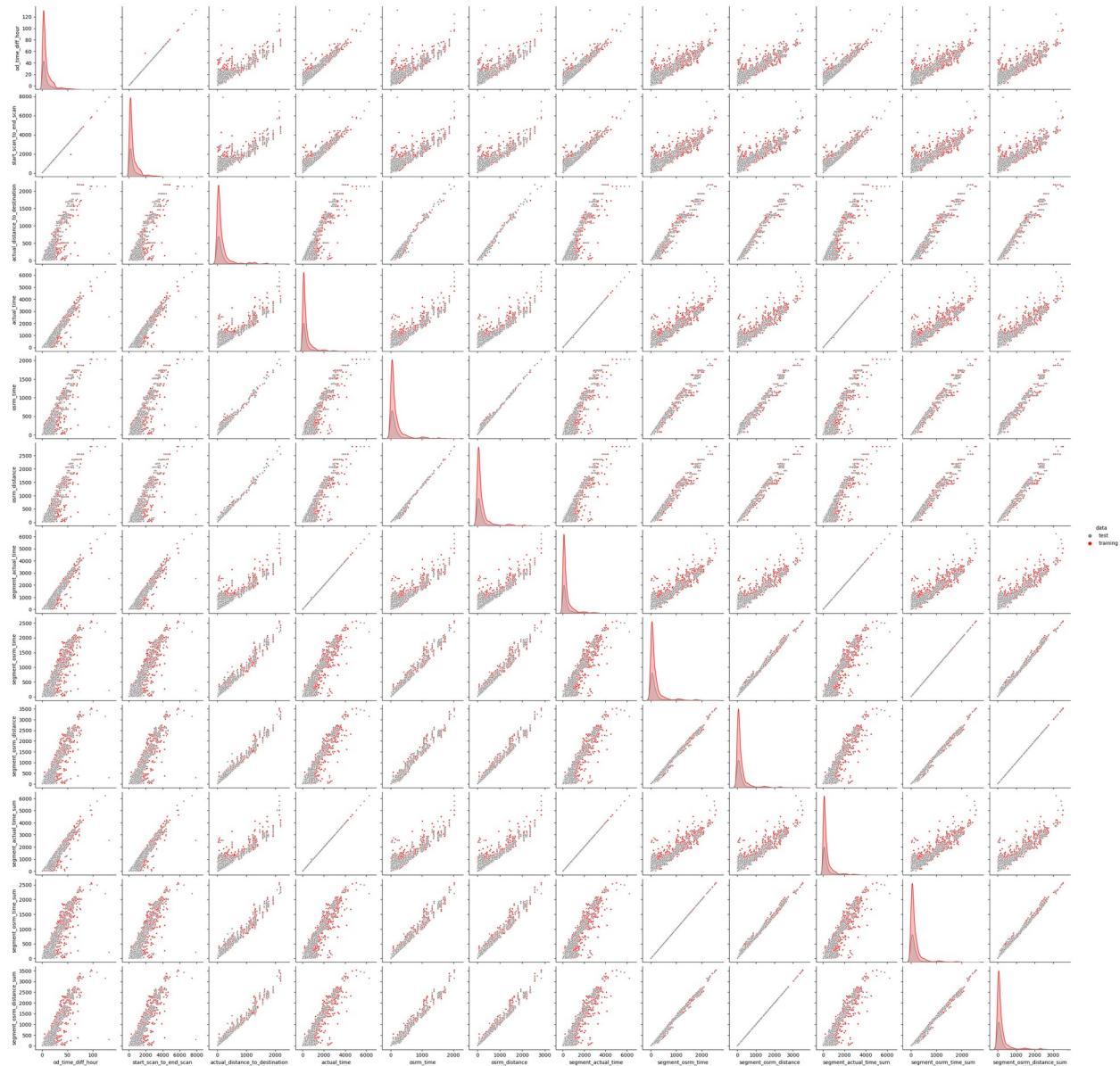
	actual_distance_to_destination	actual_time	osrm_time
osrm_distance \			
0	824.732849	1562.0	717.0
991.352295			
1	73.186905	143.0	68.0
85.111000			
2	1927.404297	3347.0	1740.0
2354.066650			
3	17.175274	59.0	15.0
19.680000			
4	127.448502	341.0	117.0
146.791794			
...
...
14782	57.762333	83.0	62.0
73.462997			
14783	15.513784	21.0	12.0
16.088200			
14784	38.684837	282.0	48.0
58.903702			
14785	134.723831	264.0	179.0
171.110306			
14786	66.081528	275.0	68.0
80.578705			

	segment_actual_time	segment_osrm_time	
segment_osrm_distance \			
0	1548.0	1008.0	1320.473267
1	141.0	65.0	84.189400
2	3308.0	1941.0	2545.267822
3	59.0	16.0	19.876600
4	340.0	115.0	146.791901
...
14782	82.0	62.0	64.855103
14783	21.0	11.0	16.088299
14784	281.0	88.0	104.886597
14785	258.0	221.0	223.532394
14786	274.0	67.0	80.578705
	segment_actual_time_sum	segment_osrm_time_sum	\
0	1548.0	1008.0	
1	141.0	65.0	
2	3308.0	1941.0	
3	59.0	16.0	
4	340.0	115.0	
...	
14782	82.0	62.0	
14783	21.0	11.0	
14784	281.0	88.0	
14785	258.0	221.0	
14786	274.0	67.0	
	segment_osrm_distance_sum		
0	1320.473267		
1	84.189400		
2	2545.267822		
3	19.876600		
4	146.791901		
...	...		
14782	64.855103		
14783	16.088299		
14784	104.886597		
14785	223.532394		
14786	80.578705		

```
[14787 rows x 12 columns]
```

```
plt.figure(figsize=(14,0.05))
plt.axis('off')
plt.title(f' Pairplot Analysis',fontfamily='serif',fontweight='bold',fontsize=15,backgroundcolor='crimson',color='w')
sns.pairplot(data = trip_df,vars = num_cols,hue='data',markers = '.',palette=cp)
plt.show()
```

Pairplot Analysis

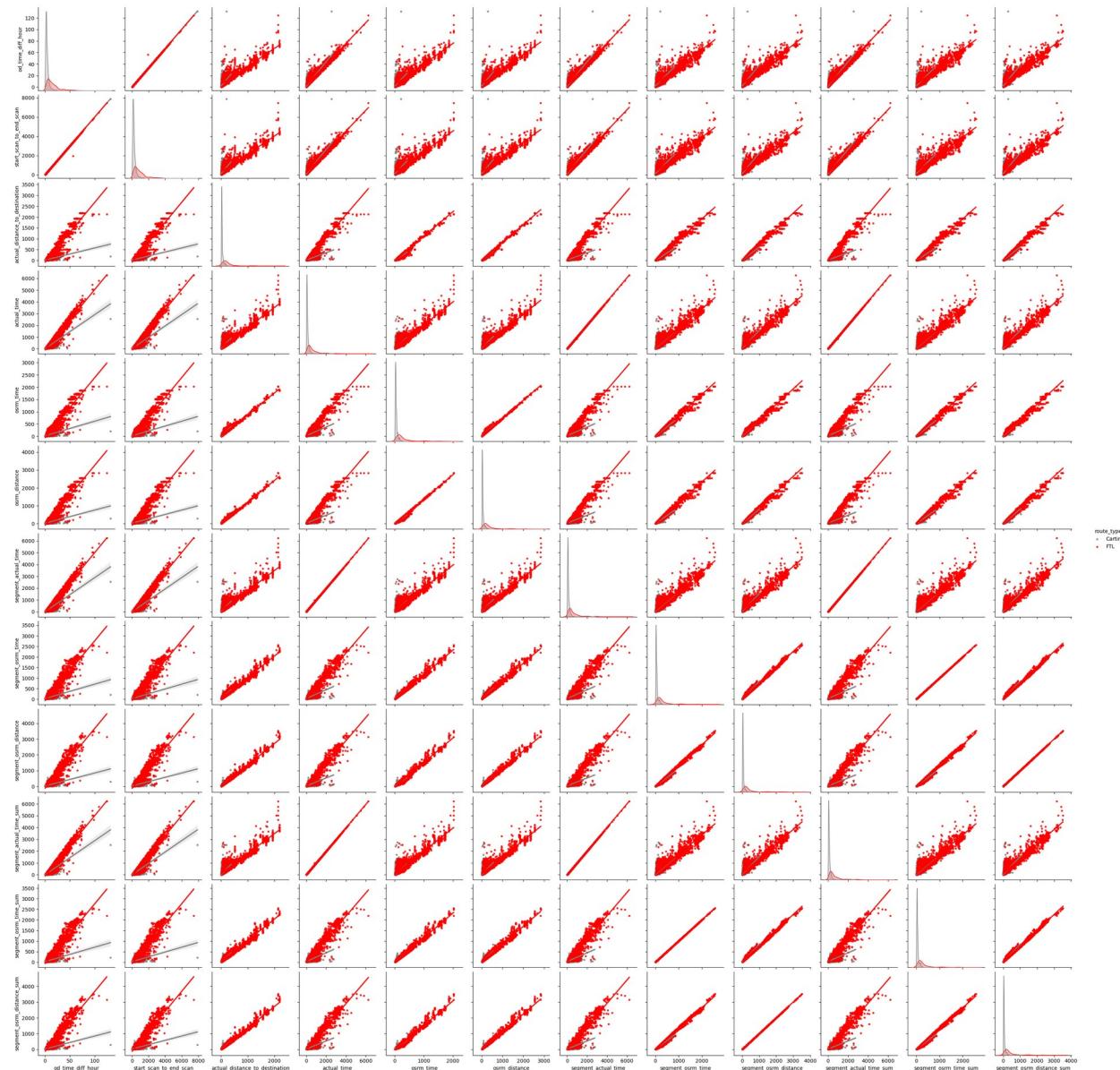


```

plt.figure(figsize=(14,0.05))
plt.axis('off')
plt.title(f' Pairplot Analysis', fontfamily='serif', fontweight='bold', fontsize=15, backgroundcolor='dimgrey', color='w')
sns.pairplot(data = trip_df, vars=num_cols, kind = 'reg',hue='route_type', markers = '.', palette=cp)
plt.show()

```

Pairplot Analysis



```

clipped_df_corr = clipped_num_df.corr()
clipped_df_corr

```

```

filtered_df_corr = filtered_num_df.corr()
filtered_df_corr

od_time_diff_hour
start_scan_to_end_scan \ od_time_diff_hour
od_time_diff_hour 1.000000
0.999837
start_scan_to_end_scan 0.999837
1.000000
actual_distance_to_destination 0.918644
0.919159
actual_time 0.961223
0.961612
osrm_time 0.926973
0.927471
osrm_distance 0.924683
0.925205
segment_actual_time 0.961288
0.961634
segment_osrm_time 0.918921
0.919429
segment_osrm_distance 0.919665
0.920191
segment_actual_time_sum 0.961288
0.961634
segment_osrm_time_sum 0.918921
0.919429
segment_osrm_distance_sum 0.919665
0.920191

actual_distance_to_destination
actual_time \
od_time_diff_hour 0.918644
0.961223
start_scan_to_end_scan 0.919159
0.961612
actual_distance_to_destination 1.000000
0.953920
actual_time 0.953920
1.000000
osrm_time 0.993568
0.958781
osrm_distance 0.997268
0.959398
segment_actual_time 0.952987
0.999989
segment_osrm_time 0.987542
0.954044
segment_osrm_distance 0.993068

```

0.957151		
segment_actual_time_sum		0.952987
0.999989		
segment_osrm_time_sum		0.987542
0.954044		
segment_osrm_distance_sum		0.993068
0.957151		
	osrm_time	osrm_distance
segment_actual_time \ od_time_diff_hour	0.926973	0.924683
0.961288		
start_scan_to_end_scan	0.927471	0.925205
0.961634		
actual_distance_to_destination	0.993568	0.997268
0.952987		
actual_time	0.958781	0.959398
0.999989		
osrm_time	1.000000	0.997588
0.957955		
osrm_distance	0.997588	1.000000
0.958540		
segment_actual_time	0.957955	0.958540
1.000000		
segment_osrm_time	0.993263	0.991802
0.953214		
segment_osrm_distance	0.991624	0.994712
0.956293		
segment_actual_time_sum	0.957955	0.958540
1.000000		
segment_osrm_time_sum	0.993263	0.991802
0.953214		
segment_osrm_distance_sum	0.991624	0.994712
0.956293		
	segment_osrm_time	
segment_osrm_distance \ od_time_diff_hour	0.918921	
0.919665		
start_scan_to_end_scan	0.919429	
0.920191		
actual_distance_to_destination	0.987542	
0.993068		
actual_time	0.954044	
0.957151		
osrm_time	0.993263	
0.991624		
osrm_distance	0.991802	
0.994712		

segment_actual_time	0.953214
0.956293	
segment_osrm_time	1.000000
0.996098	
segment_osrm_distance	0.996098
1.000000	
segment_actual_time_sum	0.953214
0.956293	
segment_osrm_time_sum	1.000000
0.996098	
segment_osrm_distance_sum	0.996098
1.000000	
	segment_actual_time_sum \
od_time_diff_hour	0.961288
start_scan_to_end_scan	0.961634
actual_distance_to_destination	0.952987
actual_time	0.999989
osrm_time	0.957955
osrm_distance	0.958540
segment_actual_time	1.000000
segment_osrm_time	0.953214
segment_osrm_distance	0.956293
segment_actual_time_sum	1.000000
segment_osrm_time_sum	0.953214
segment_osrm_distance_sum	0.956293
	segment_osrm_time_sum \
od_time_diff_hour	0.918921
start_scan_to_end_scan	0.919429
actual_distance_to_destination	0.987542
actual_time	0.954044
osrm_time	0.993263
osrm_distance	0.991802
segment_actual_time	0.953214
segment_osrm_time	1.000000
segment_osrm_distance	0.996098
segment_actual_time_sum	0.953214
segment_osrm_time_sum	1.000000
segment_osrm_distance_sum	0.996098
	segment_osrm_distance_sum
od_time_diff_hour	0.919665
start_scan_to_end_scan	0.920191
actual_distance_to_destination	0.993068
actual_time	0.957151
osrm_time	0.991624
osrm_distance	0.994712
segment_actual_time	0.956293
segment_osrm_time	0.996098

```

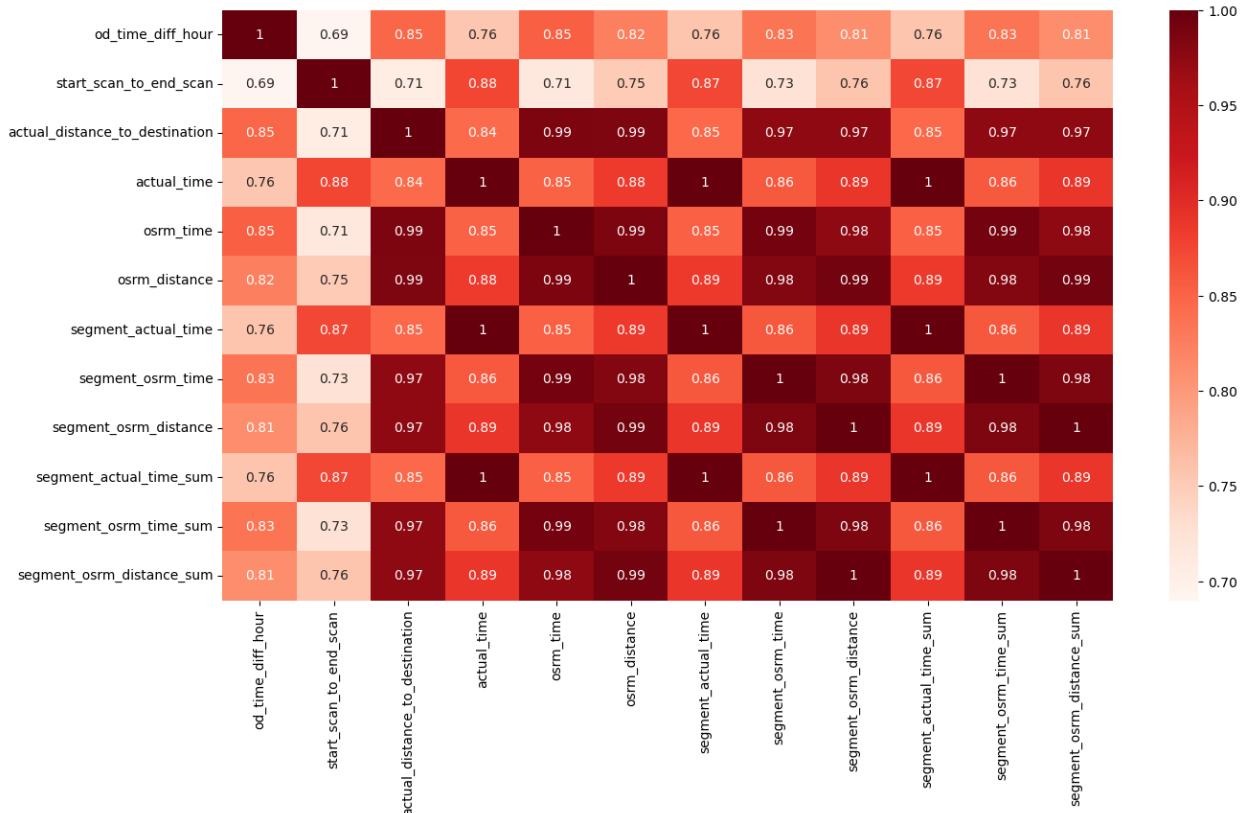
segment_osrm_distance 1.000000
segment_actual_time_sum 0.956293
segment_osrm_time_sum 0.996098
segment_osrm_distance_sum 1.000000

plt.figure(figsize = (15,8))
plt.suptitle(f'Correlation Analysis -  
clipped_df',fontfamily='serif',fontweight='bold',fontsize=15,backgroundcolor='k',color='w')
sns.heatmap(data = clipped_df_corr,vmin=0.69, annot = True, cmap='Reds')
plt.show()

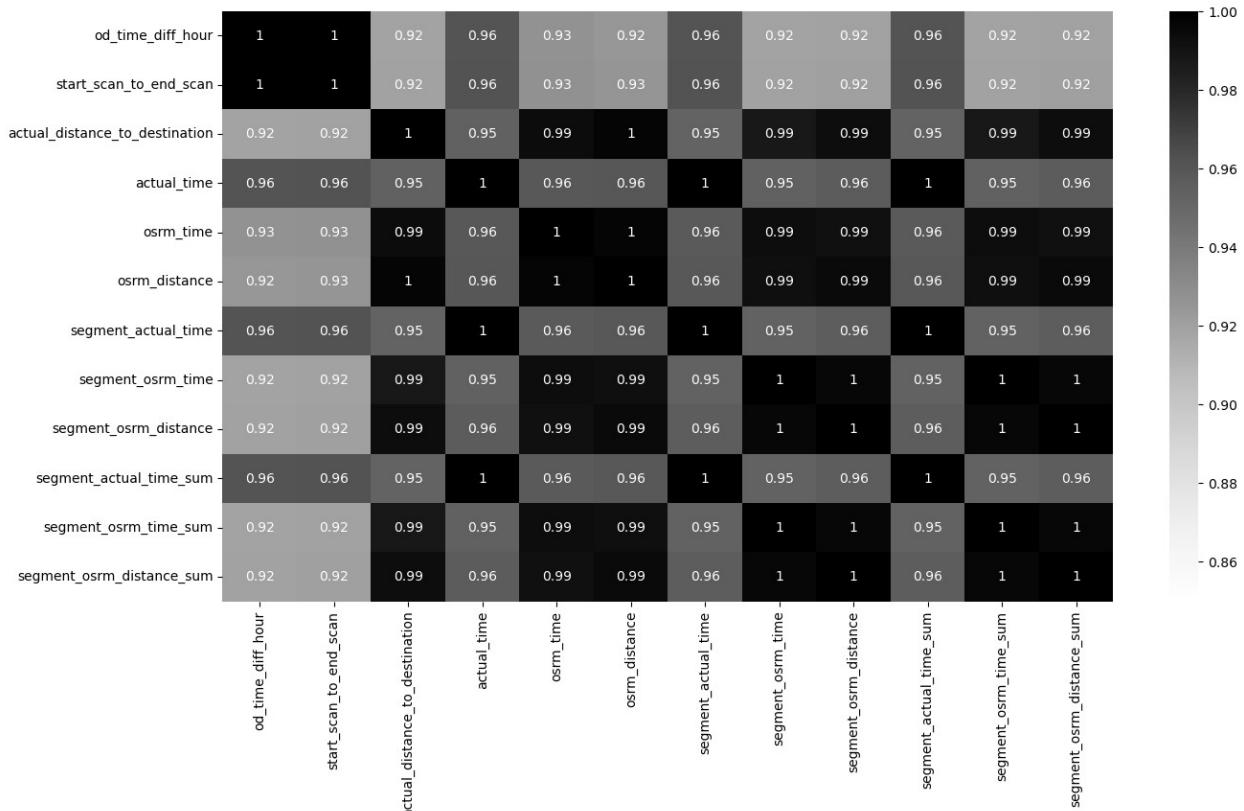
plt.figure(figsize = (15,8))
plt.suptitle(f'Correlation Analysis -  
filtered_df',fontfamily='serif',fontweight='bold',fontsize=15,backgroundcolor='r',color='w')
sns.heatmap(data = filtered_df_corr,vmin=0.85, annot = True, cmap='Greys')
plt.show()

```

Correlation Analysis- clipped_df



Correlation Analysis - filtered_df



Insights:

- Very High Correlation exists between all the numerical columns.

```
trip_df.skew(numeric_only = True)
```

od_time_diff_hour	2.893550
trip_creation_month	2.337439
trip_creation_year	0.000000
trip_creation_day	-0.695241
trip_creation_hour	-0.206092
trip_creation_weekday	0.065904
trip_creation_week	0.181308
start_scan_to_end_scan	2.895337
actual_distance_to_destination	3.562931
actual_time	3.375178
osrm_time	3.455256
osrm_distance	3.553619
segment_actual_time	3.372043
segment_osrm_time	3.602915
segment_osrm_distance	3.714016
segment_actual_time_sum	3.372043

```

segment_osrm_time_sum           3.602915
segment_osrm_distance_sum       3.714016
trip_creation_dayofdate        -0.695241
dtype: float64

```

Insights:

- We can see that Many of the data is *Right-Skewed*.

1one-hot encoding

```

trip_df.info()

categorical_cols = ['data','route_type']

# one hot encoding the categorical features
ohe = OneHotEncoder(sparse=False)
encoded_cat_cols = ohe.fit_transform(trip_df[categorical_cols])

categorical_encoded_df = pd.DataFrame(encoded_cat_cols,
columns=ohe.get_feature_names_out(categorical_cols))
display(categorical_encoded_df)

encoded_df = pd.concat([trip_df,categorical_encoded_df],axis=1)
encoded_df

      data_test  data_training  route_type_Carting  route_type_FTL
0            0.0          1.0              0.0             1.0
1            0.0          1.0              1.0             0.0
2            0.0          1.0              0.0             1.0
3            0.0          1.0              1.0             0.0
4            0.0          1.0              0.0             1.0
...
14782         1.0          0.0              1.0             0.0
14783         1.0          0.0              1.0             0.0
14784         1.0          0.0              1.0             0.0
14785         1.0          0.0              1.0             0.0
14786         1.0          0.0              0.0             1.0

[14787 rows x 4 columns]

      trip_uuid    data route_type \
0  trip-153671041653548748  training      FTL
1  trip-153671042288605164  training    Carting
2  trip-153671043369099517  training      FTL
3  trip-153671046011330457  training    Carting
4  trip-153671052974046625  training      FTL
...
14782  trip-153861095625827784      test    Carting
14783  trip-153861104386292051      test    Carting
14784  trip-153861106442901555      test    Carting

```

	trip_id	test	Carting	
14785	trip-153861115439069069	test	Carting	
14786	trip-153861118270144424	test	FTL	
0	od_start_time	od_end_time	\	
1	2018-09-12 16:39:46.858469	2018-09-12 16:39:46.858469		
2	2018-09-12 02:03:09.655591	2018-09-12 02:03:09.655591		
3	2018-09-14 03:40:17.106733	2018-09-14 03:40:17.106733		
4	2018-09-12 00:01:00.113710	2018-09-12 01:41:29.809822		
5	2018-09-12 00:02:09.740725	2018-09-12 03:54:43.114421		
...		
14782	2018-10-03 23:55:56.258533	2018-10-04 06:41:25.409035		
14783	2018-10-03 23:57:23.863155	2018-10-04 00:57:59.294434		
14784	2018-10-04 02:51:27.075797	2018-10-04 02:51:27.075797		
14785	2018-10-03 23:59:14.390954	2018-10-04 02:29:04.272194		
14786	2018-10-04 03:58:40.726547	2018-10-04 03:58:40.726547		
0	od_time_diff_hour	trip_creation_time		
1	trip_creation_month	\		
2	37.668497	2018-09-12 00:00:16.535741		
3	9			
4	1	3.026865	2018-09-12 00:00:22.886430	
5	9			
6	2	65.572709	2018-09-12 00:00:33.691250	
7	9			
8	3	1.674916	2018-09-12 00:01:00.113710	
9	9			
10	4	11.972484	2018-09-12 00:02:09.740725	
11	9			
12	
13	
14	14782	4.300482	2018-10-03 23:55:56.258533	
15	10			
16	14783	1.009842	2018-10-03 23:57:23.863155	
17	10			
18	14784	7.035331	2018-10-03 23:57:44.429324	
19	10			
20	14785	5.808548	2018-10-03 23:59:14.390954	
21	10			
22	14786	5.906793	2018-10-03 23:59:42.701692	
23	10			
0	trip_creation_year	trip_creation_day	trip_creation_hour	\
1	2018	12	0	
2	2018	12	0	
3	2018	12	0	
4	2018	12	0	
5	
6	14782	2018	3	23
7	14783	2018	3	23

14784	2018	3	23
14785	2018	3	23
14786	2018	3	23
trip_creation_weekday		trip_creation_week	
start_scan_to_end_scan \			
0	2	37	
2259.0			
1	2	37	
180.0			
2	2	37	
3933.0			
3	2	37	
100.0			
4	2	37	
717.0			
...
..			
14782	2	40	
257.0			
14783	2	40	
60.0			
14784	2	40	
421.0			
14785	2	40	
347.0			
14786	2	40	
353.0			
actual_distance_to_destination		actual_time	osrm_time
osrm_distance \			
0	824.732849	1562.0	717.0
991.352295			
1	73.186905	143.0	68.0
85.111000			
2	1927.404297	3347.0	1740.0
2354.066650			
3	17.175274	59.0	15.0
19.680000			
4	127.448502	341.0	117.0
146.791794			
...
..			
14782	57.762333	83.0	62.0
73.462997			
14783	15.513784	21.0	12.0
16.088200			
14784	38.684837	282.0	48.0
58.903702			

14785	134.723831	264.0	179.0
171.110306			
14786	66.081528	275.0	68.0
80.578705			
	segment_actual_time	segment_osrm_time	
	segment_osrm_distance	\	
0	1548.0	1008.0	1320.473267
1	141.0	65.0	84.189400
2	3308.0	1941.0	2545.267822
3	59.0	16.0	19.876600
4	340.0	115.0	146.791901
...
14782	82.0	62.0	64.855103
14783	21.0	11.0	16.088299
14784	281.0	88.0	104.886597
14785	258.0	221.0	223.532394
14786	274.0	67.0	80.578705
	segment_actual_time_sum	segment_osrm_time_sum	\
0	1548.0	1008.0	
1	141.0	65.0	
2	3308.0	1941.0	
3	59.0	16.0	
4	340.0	115.0	
...	
14782	82.0	62.0	
14783	21.0	11.0	
14784	281.0	88.0	
14785	258.0	221.0	
14786	274.0	67.0	
	segment_osrm_distance_sum		source_name
\			
0	1320.473267	Kanpur_Central_H_6 (Uttar Pradesh)	
1	84.189400	Doddablpur_Chikadpp_D (Karnataka)	
2	2545.267822	Gurgaon_Bilaspur_HB (Haryana)	

3	19.876600	Mumbai Hub (Maharashtra)
4	146.791901	Bellary_Dc (Karnataka)
...
14782	64.855103	Chandigarh_Mehmdpur_H (Punjab)
14783	16.088299	FBD_Balabgarh_DPC (Haryana)
14784	104.886597	Kanpur_GovndNgr_DC (Uttar Pradesh)
14785	223.532394	Tirunelveli_VdkkuSrt_I (Tamil Nadu)
14786	80.578705	Sandur_WrdN1DPP_D (Karnataka)
source_city source_state source_place \		
0 Kanpur	Uttar Pradesh	Central_H_6
1 Doddablpur	Karnataka	ChikaDPP_D
2 Gurgaon	Haryana	Bilaspur_HB
3 Mumbai	Maharashtra	Hub
4 Bellary	Karnataka	Dc
...
14782 Chandigarh	Punjab	Mehmdpur_H
14783 FBD	Haryana	Balabgarh_DPC
14784 Kanpur	Uttar Pradesh	GovndNgr_DC
14785 Tirunelveli	Tamil Nadu	VdkkuSrt_I
14786 Sandur	Karnataka	WrdN1DPP_D
destination_name destination_city		
destination_state \		
0 Gurgaon_Bilaspur_HB (Haryana)	Gurgaon	
Haryana		
1 Chikblapur_ShntiSgr_D (Karnataka)	Chikblapur	
Karnataka		
2 Chandigarh_Mehmdpur_H (Punjab)	Chandigarh	
Punjab		
3 Mumbai_MiraRd_IP (Maharashtra)	Mumbai	
Maharashtra		
4 Hospet (Karnataka)	Hospet	
Karnataka		
...
...		
14782 Zirakpur_DC (Punjab)	Zirakpur	
Punjab		
14783 Faridabad_Blbgarh_DC (Haryana)	Faridabad	
Haryana		
14784 Kanpur_Central_H_6 (Uttar Pradesh)	Kanpur	Uttar
Pradesh		

```

14785      Eral_Busstand_D (Tamil Nadu)           Eral
Tamil Nadu
14786      Bellary_Dc (Karnataka)               Bellary
Karnataka

    destination_place
corridor \
0      Bilaspur_HB  Kanpur_Central_H_6 (Uttar Pradesh) <-->
Gurga...
1      ShntiSgr_D  Doddablpur_ChikaDPP_D (Karnataka) <-->
Chikbl...
2      Mehmdpur_H  Gurgaon_Bilaspur_HB (Haryana) <-->
Chandigarh...
3      MiraRd_IP   Mumbai Hub (Maharashtra) <-->
Mumbai_MiraRd_I...
4      Hospet      Bellary_Dc (Karnataka) <--> Hospet
(Karnataka)
...
...
14782      DC  Chandigarh_Mehmdpur_H (Punjab) <-->
Zirakpur...
14783      Blbgarh_DC  FBD_Balabgarh_DPC (Haryana) <-->
Faridabad_B...
14784      Central_H_6  Kanpur_GovndNgr_DC (Uttar Pradesh) <-->
Kanpu...
14785      Busstand_D  Tirunelveli_VdkkuSrt_I (Tamil Nadu) <-->
Eral...
14786      Dc  Sandur_WrdN1DPP_D (Karnataka) <-->
Bellary_Dc...

    state_corridor \
0      Uttar Pradesh--Kanpur <--> Haryana--Gurgaon
1      Karnataka--Doddablpur <--> Karnataka--Chiklapur
2      Haryana--Gurgaon <--> Punjab--Chandigarh
3      Maharashtra--Mumbai <--> Maharashtra--Mumbai
4      Karnataka--Bellary <--> Karnataka--Hospet
...
14782      Punjab--Chandigarh <--> Punjab--Zirakpur
14783      Haryana--FBD <--> Haryana--Faridabad
14784      Uttar Pradesh--Kanpur <--> Uttar Pradesh--Kanpur
14785      Tamil Nadu--Tirunelveli <--> Tamil Nadu--Eral
14786      Karnataka--Sandur <--> Karnataka--Bellary

    city_corridor \
0      Kanpur--Central_H_6 <--> Gurgaon--Bilaspur_HB
1      Doddablpur--ChikaDPP_D <--> Chiklapur--Shnti...
2      Gurgaon--Bilaspur_HB <--> Chandigarh--Mehmdpur_H
3      Mumbai--Hub <--> Mumbai--MiraRd_IP
4      Bellary--Dc <--> Hospet--Hospet
...

```

```

14782      Chandigarh--Mehmdpur_H <---> Zirakpur--DC
14783      FBD--Balabgarh_DPC <---> Faridabad--Blbgarh_DC
14784      Kanpur--GovndNgr_DC <---> Kanpur--Central_H_6
14785      Tirunelveli--VdkkuSrt_I <---> Eral--Busstand_D
14786      Sandur--WrdN1DPP_D <---> Bellary--Dc

    trip_creation_day_week  trip_creation_dayofdate  data_test \
0                  Wednesday                      12     0.0
1                  Wednesday                      12     0.0
2                  Wednesday                      12     0.0
3                  Wednesday                      12     0.0
4                  Wednesday                      12     0.0
...
14782                 ...
14783                 ...
14784                 ...
14785                 ...
14786                 ...

    data_training  route_type_Carting  route_type_FTL
0            1.0           0.0           1.0
1            1.0           1.0           0.0
2            1.0           0.0           1.0
3            1.0           1.0           0.0
4            1.0           0.0           1.0
...
14782            ...
14783            ...
14784            ...
14785            ...
14786            ...

[14787 rows x 41 columns]

```

##Minmax scaler

[]Most appropriate since the data is not gaussian

```

# Normalizing/Standardizing the numerical features using MinMaxScaler
min_max_scaler = MinMaxScaler()
min_max_scaled_numerical =
min_max_scaler.fit_transform(trip_df[num_cols])

# Converting the scaled features back to a dataframe
min_max_scaled_df = pd.DataFrame(min_max_scaled_numerical,
columns=num_cols)
min_max_scaled_df

    od_time_diff_hour  start_scan_to_end_scan \
0              0.284016          0.283937

```

	actual_distance_to_destination	actual_time	osrm_time
osrm_distance \			
0	0.374613	0.248242	0.350938
0.346972			
1	0.029476	0.021419	0.030602
0.026859			
2	0.880999	0.533568	0.855874
0.828325			
3	0.003753	0.007992	0.004442
0.003747			
4	0.054395	0.053069	0.054788
0.048647			
...
...			
14782	0.022392	0.011829	0.027641
0.022745			
14783	0.002990	0.001918	0.002962
0.002478			
14784	0.013631	0.043638	0.020731
0.017602			
14785	0.057736	0.040761	0.085390
0.057237			
14786	0.026213	0.042519	0.030602
0.025258			
segment_osrm_distance \			
0	0.247388	0.391712	0.373134
1	0.021218	0.023065	0.021373
2	0.530301	0.756450	0.721625
3	0.008037	0.003909	0.003074
4	0.053207	0.042611	0.039185
...

14782	0.011734	0.021892	0.015872
14783	0.001929	0.001955	0.001996
14784	0.043723	0.032056	0.027262
14785	0.040026	0.084050	0.061020
14786	0.042598	0.023847	0.020346

	segment_actual_time_sum	segment_osrm_time_sum	\
0	0.247388	0.391712	
1	0.021218	0.023065	
2	0.530301	0.756450	
3	0.008037	0.003909	
4	0.053207	0.042611	
...	
14782	0.011734	0.021892	
14783	0.001929	0.001955	
14784	0.043723	0.032056	
14785	0.040026	0.084050	
14786	0.042598	0.023847	

	segment_osrm_distance_sum
0	0.373134
1	0.021373
2	0.721625
3	0.003074
4	0.039185
...	...
14782	0.015872
14783	0.001996
14784	0.027262
14785	0.061020
14786	0.020346

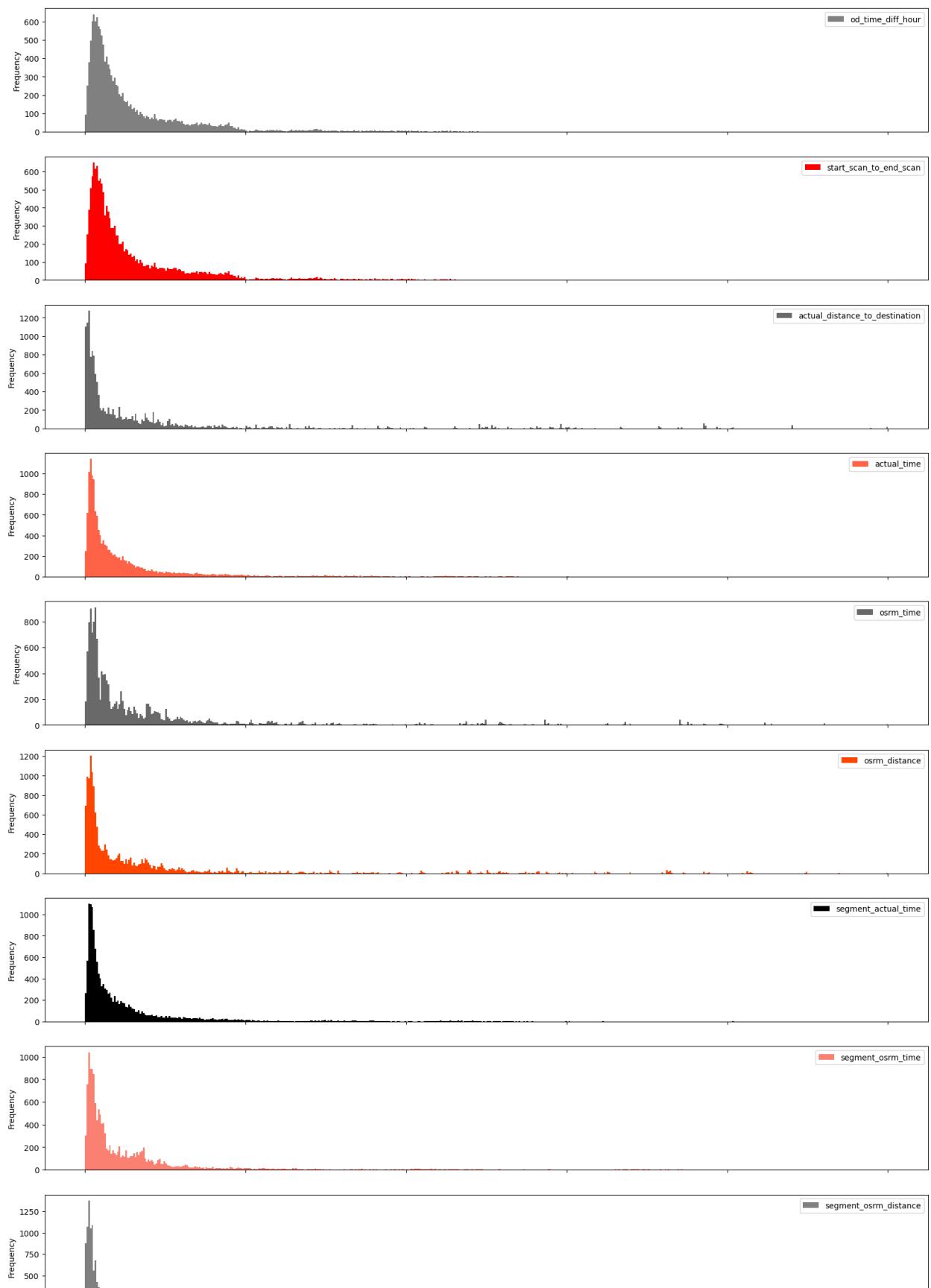
[14787 rows x 12 columns]

```

plt.figure(figsize=(14,0.05))
plt.axis('off')
plt.suptitle(f'Min-Max scaled visualization of num_cols',fontfamily='serif',fontweight='bold',fontsize=15,backgroundcolor='k',color='w')
min_max_scaled_df.plot(kind='hist',
figsize=(20,40),subplots=True,color=cp,bins=500)
plt.show()

```

Min-Max scaled visualization of num_cols



```

# Just so to know ... cant do this as `data is not gaussian`
# Standardization works only with data which follows normal
distribution
# Standardizing the numerical features using StandardScaler
std_scaler = StandardScaler()
std_scaled = std_scaler.fit_transform(trip_df[num_cols])

# Converting the scaled features back to a dataframe
std_scaled_df = pd.DataFrame(std_scaled, columns=num_cols)
std_scaled_df

      od_time_diff_hour  start_scan_to_end_scan \
0           2.625886            2.627598
1          -0.529518           -0.530859
2           5.167598            5.170772
3          -0.652664           -0.652397
4           0.285312            0.284962
..          ...
14782       -0.413508           -0.413880
14783       -0.713243           -0.713166
14784       -0.164399           -0.164728
14785       -0.276143           -0.277150
14786       -0.267194           -0.268034

      actual_distance_to_destination  actual_time  osrm_time
osrm_distance \
0                           2.162548    2.147277   2.048290
2.125107
1                           -0.297563   -0.379887  -0.342571
0.320538
2                           5.772034    5.326268   5.816936
5.802622
3                           -0.480911   -0.529486  -0.537818
0.497115
4                           -0.119943   -0.027259  -0.162059
0.154082
..          ...
14782       -0.348054   -0.486744  -0.364674
0.351972
14783       -0.486350   -0.597162  -0.548870
0.506808
14784       -0.410502   -0.132335  -0.416249
0.391263
14785       -0.096128   -0.164392   0.066344
0.088455
14786       -0.320822   -0.144802  -0.342571
0.332769

      segment_actual_time  segment_osrm_time

```

segment_osrm_distance \			
0	2.147833	2.629714	2.633597
1	-0.381163	-0.367090	-0.332307
2	5.311326	5.594737	5.571936
3	-0.528553	-0.522809	-0.486596
4	-0.023473	-0.208192	-0.182120
...
14782	-0.487212	-0.376623	-0.378690
14783	-0.596856	-0.538699	-0.495684
14784	-0.129522	-0.293997	-0.282653
14785	-0.170863	0.128670	0.001984
14786	-0.142104	-0.360734	-0.340969

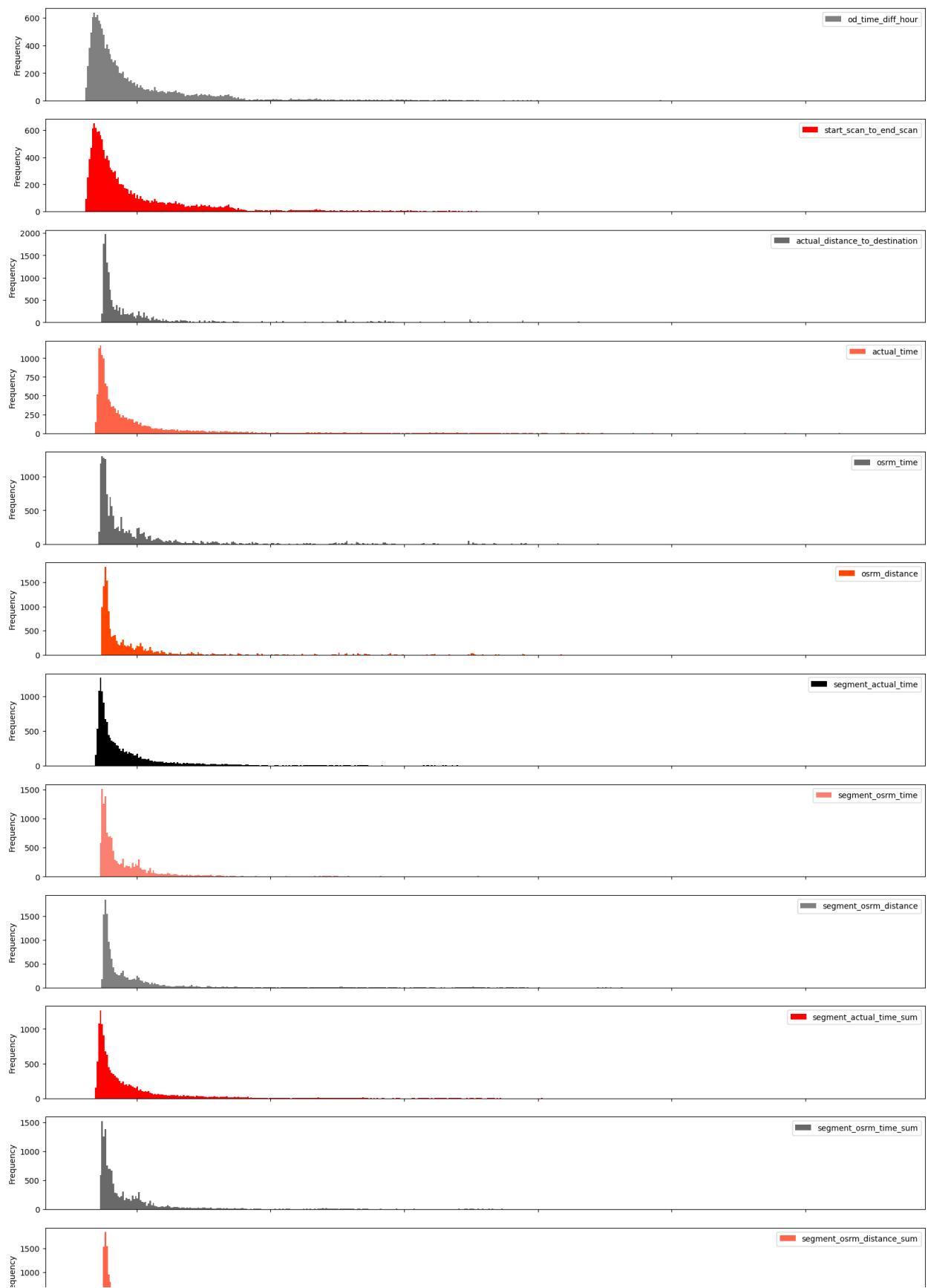
segment_actual_time_sum	segment_osrm_time_sum \
0	2.147833
1	-0.381163
2	5.311326
3	-0.528553
4	-0.023473
...	...
14782	-0.487212
14783	-0.596856
14784	-0.129522
14785	-0.170863
14786	-0.142104

segment_osrm_distance_sum	
0	2.633597
1	-0.332307
2	5.571936
3	-0.486596
4	-0.182120
...	...
14782	-0.378690
14783	-0.495684
14784	-0.282653
14785	0.001984
14786	-0.340969

[14787 rows x 12 columns]

```
plt.figure(figsize=(14,0.05))
plt.axis('off')
plt.suptitle(f'Standardized Num_cols scaled  
visualization',fontfamily='serif',fontweight='bold',fontsize=15,backgroundcolor='r',color='w')
std_scaled_df.plot(kind='hist',
figsize=(20,30),subplots=True,color=cp,bins=500)
plt.show()
```

Standardized Num_cols scaled visualization



Hypothesis Testing:

- Perform hypothesis testing / visual analysis between :
 - actual_time aggregated value and OSRM time aggregated value.
 - actual_time aggregated value and segment actual time aggregated value.
 - OSRM distance aggregated value and segment OSRM distance aggregated value.
 - OSRM time aggregated value and segment OSRM time aggregated value.
- Note: Aggregated values are the values you'll get after merging the rows on the basis of trip_uuid.

Assumptions of T-Test

1. The sample size should be less than 30.
2. The population variance is unknown.
3. The population mean and standard deviation are finite.
4. The means of the two populations being compared should follow normal distributions.
5. If using Student's original definition of the t-test, the two populations being compared should have the same variance. If the sample sizes in the two groups being compared are equal, Student's original t-test is highly robust to the presence of unequal variances.

STEP-1: Set up Null Hypothesis

Null Hypothesis (H₀) - There is no significant difference in the mean values between column1 and column2

$$H_0: \mu_{col1} = \mu_{col2}$$

Alternate Hypothesis (H_a) - There is a significant difference in the mean values between column1 and column2

$$H_a: \mu_{col1} \neq \mu_{col2}$$

STEP-2: Checking for basic assumptions for the hypothesis

Normality checks

- Distribution check using **QQ Plot & prob Plot**
 - Confirmation by **Shapiro-wilks Test**
 - Confirmation by **Anderson-darling Test**
 - Homogeneity of Variances using **Levene's test**
-

STEP-3: Define Test statistics; Distribution of T under H₀.

- We know that the test statistic while performing a T-Test follows T-distribution.
for independent variables:

```
>>If data follows normal distribution we go with **ttest_ind**  
>> Else we will go with **Mannwhitney_u test** (Non - Parametric test)
```

for dependent variables: (paired T-test)

```
>>If data follows normal distribution we go with **ttest_rel**  
>>Else we will go with **Wilcoxon signed rank test** (Non - Parametric  
test)
```

STEP-4: Decide the kind of test.

- We will be performing **Two tailed t-test**

STEP-5: Compute the p-value and fix value of alpha.

- we will be computing the t-stat value using the ttest function using scipy.stats.
- We set our **alpha to be 0.05 (i.e) confidence level = 95%**

STEP-6: Compare p-value and alpha.

- Based on p-value, we will accept or reject H0.

p-val < alpha : Reject H0

p-val > alpha : Accept H0

```
# def shapiro_and_anderson(name,col):  
  
#     print(f"Performing SHAPIRO & ANDERSON DARLING TEST for {name}  
column")  
#     print()  
#     print('Shapiro Wilks Test')  
#     shapiro_stat , p_val = shapiro(col)  
#     if p_val < 0.05:  
#         print(f'{name} - Data is not Gaussian')  
#     else:  
#         print(f'{name} - Data is Gaussian')  
#     print()  
  
#     print("As shapiro is sensitive, we go with ANDERSON DARLING  
TEST")  
#     result = anderson(col)  
#     if result.statistic > result.critical_values[2]:  
#         print(f'{name} - Data does not follow normal distribution.')  
#     else:  
#         print(f'{name} - Data follows normal distribution.')  
#     print()  
#     print('*'*50)  
  
#     def boxcox_transformation(name,col):
```

```

#             print(f'Performing BOXCOX transformation on {name} column')
#             transformed_data,best_lambda = boxcox(col)

#             return " "

# class NormalCheck:
#     def __init__(self, name, col):
#         self.name = name
#         self.col = col

#     def perform_checks(self):
#         boxcox_transformation(self.name, self.col)
#         shapiro_and_anderson(self.name, self.col)

class Normality_check:
    def __init__(self, name, col):
        self.name = name
        self.col = col

    def shapiro_and_anderson(self):
        print(f"Performing SHAPIRO & ANDERSON-DARLING TEST for
{self.name} column")
        print()

        # Shapiro-Wilk Test
        print('Shapiro-Wilk Test')
        shapiro_stat, p_val = shapiro(self.col)
        if p_val < 0.05:
            print(f'{self.name} - Data is not Gaussian')
        else:
            print(f'{self.name} - Data is Gaussian')
        print()

        # Using Anderson-Darling Test
        print("Since Shapiro-Wilk test is sensitive, we go with
Anderson-Darling Test")
        result = anderson(self.col)
        if result.statistic > result.critical_values[2]:
            print(f'{self.name} - Data does not follow a normal
distribution.')
        else:
            print(f'{self.name} - Data follows a normal
distribution.')
        print()
        print('*'*50)

    def boxcox_transformation(self):
        print(f'Performing BOXCOX transformation on {self.name}
column')

```

```

        transformed_data, best_lambda = boxcox(self.col)
        self.col = transformed_data # Update column data with
transformed data
        self.shapiro_and_anderson() # Calling shapiro_and_anderson
method after transformation

# normality_check = NormalCheck(name, col)
# normality_check.boxcox_transformation()

def levene_test(name1,name2,col1,col2):
    levene_stat, p_value = levene(col1,col2)

    print(f'Performing Levene Test for {name1} & {name2} ')

    if p_value < 0.05:
        print('Does not have Homogenous (different) Variance')
    else:
        print('Have Homogenous (similar) variance')
    print()
    print('-'*50)
    print()
    return ""

## MannWhitney u Rank test
### Test statistics : Mann-Whitney U rank test for two independent
samples

def mannwhitneyu_test(name1,name2,col1,col2):
    print(f'Performing Non-parametric Test - MannWhitneyU for {name1}
& {name2}')
    test_stat, p_value = mannwhitneyu(col1,col2)

    if p_value < 0.05:
        print("Reject Null Hypothesis")
        print(f'There is a significant difference in the Mean values
of {name1} and {name2}')
    else:
        print("Failed to Reject Null Hypothesis - Accept H0")
        print(f'There is NO significant difference in the Mean values
of {name1} and {name2}')

    print()
    print('-'*50)
    print()

    return ""

```

```

def normality_plots(name1,name2,name3,name4,col1,col2,col3,col4):

    plt.figure(figsize = (20,10))
    plt.suptitle("Normality check - Histplot &
QQ(prob)plot",fontsize=16,fontweight="bold",backgroundcolor=cp[5],color='w')

    plt.subplot(241)
    sns.histplot(col1, element = 'step', color =cp[1], kde = True,
label = name1)
    plt.title(f'Histplot -
{name1}',fontsize=10,fontweight="bold",backgroundcolor=cp[1],color='w')
)
    plt.legend()

    plt.subplot(242)
    sns.histplot(col3,element = 'step', color = cp[2], kde = True,
label = name3 )
    plt.title(f'Histplot -
{name3}',fontsize=10,fontweight="bold",backgroundcolor=cp[2],color='w')
)
    plt.legend()

    plt.subplot(243)
    probplot(col1, plot = plt, dist = 'norm')
    plt.title(f'Probplot -
{name1}',fontsize=10,fontweight="bold",backgroundcolor=cp[1],color='w')
)

    plt.subplot(244)
    probplot(col3, plot = plt, dist = 'norm')
    plt.title(f'Probplot -
{name3}',fontsize=10,fontweight="bold",backgroundcolor=cp[2],color='w'
)

    plt.subplot(245)
    sns.histplot(col2, element = 'step', color =cp[1], kde = True,
label = name2 )
    plt.title(f'Histplot -
{name2}',fontsize=10,fontweight="bold",backgroundcolor=cp[1],color='w'
)
    plt.legend()

    plt.subplot(246)
    sns.histplot(col4,element = 'step', color = cp[2], kde = True,
label = name4)
    plt.title(f'Histplot -
{name4}',fontsize=10,fontweight="bold",backgroundcolor=cp[2],color='w'
)
    plt.legend()

```

```

plt.subplot(247)
probplot(col2, plot = plt, dist = 'norm')
plt.title(f'Probplot - {name2}', fontsize=10, fontweight="bold", backgroundcolor=cp[1], color='w')
)

plt.subplot(248)
probplot(col4, plot = plt, dist = 'norm')
plt.title(f'Probplot - {name4}', fontsize=10, fontweight="bold", backgroundcolor=cp[2], color='w')
)

sns.despine()
plt.show()

```

Hypothesis testing - actual_time aggregated value and OSRM time aggregated value.

```
clipped_num_df.sample(3)
```

	od_time_diff_hour	start_scan_to_end_scan	\
4578	10.118006	543.285302	
176	1.358135	81.000000	
505	6.646569	398.000000	

osrm_distance \	actual_distance_to_destination	actual_time	osrm_time
4578	220.068207	353.0	221.0
249.271805			
176	9.083277	28.0	11.0
14.245600			
505	101.146736	259.0	98.0
130.815598			

	segment_actual_time	segment_osrm_time	segment_osrm_distance	\
4578	351.0	238.0	272.674194	
176	28.0	11.0	14.245600	
505	257.0	115.0	130.997910	

	segment_actual_time_sum	segment_osrm_time_sum	\
4578	351.0	238.0	
176	28.0	11.0	
505	257.0	115.0	

	segment_osrm_distance_sum
4578	272.674194
176	14.245600
505	130.997910

```

clipped_num_df[['actual_time','osrm_time']].describe().T
      count      mean       std    min    25%    50%    75%
\\
actual_time  14787.0  224.212577  185.922840  9.0   67.0  148.0  367.0
osrm_time    14787.0  128.190912  150.301267  6.0   29.0  60.0  168.0

                           max
actual_time  543.285302
osrm_time    543.285302

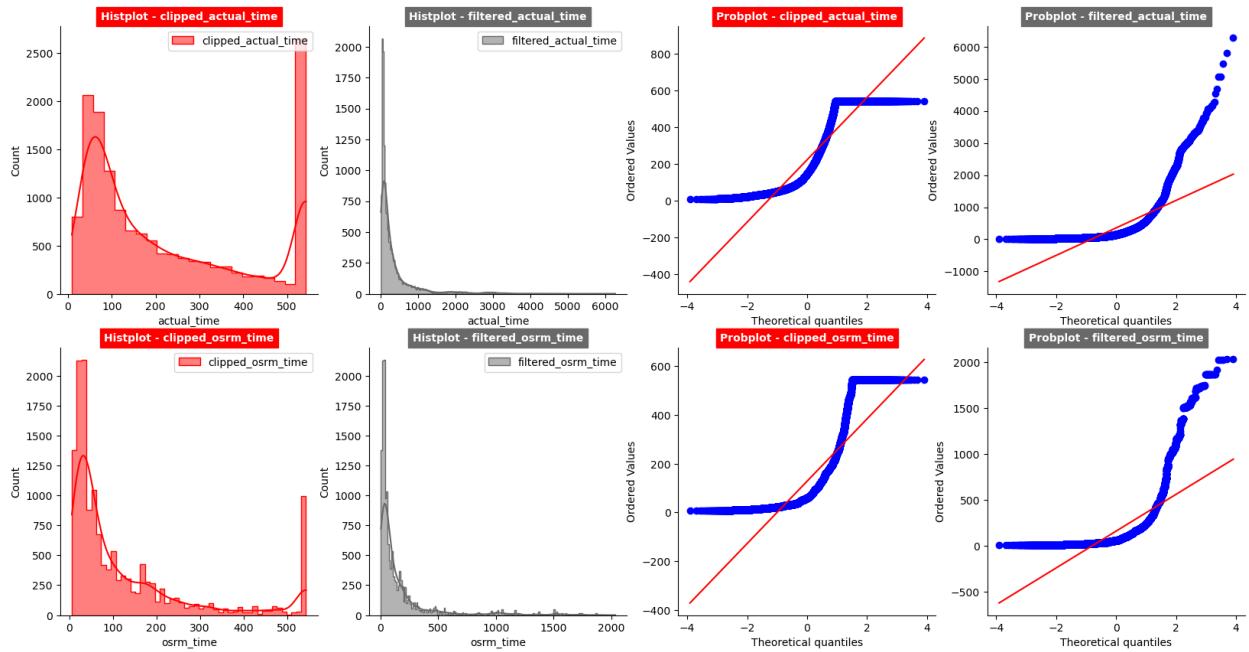
filtered_num_df[['actual_time','osrm_time']].describe().T
      count      mean       std    min    25%    50%    75%
max
actual_time  14787.0  356.306000  561.517761  9.0   67.0  148.0  367.0
6265.0
osrm_time    14787.0  160.990936  271.459229  6.0   29.0  60.0  168.0
2032.0

actual_time = clipped_num_df['actual_time']
osrm_time = clipped_num_df['osrm_time']
fil_actual_time = filtered_num_df['actual_time']
fil_osrm_time = filtered_num_df['osrm_time']

normality_plots('clipped_actual_time','clipped_osrm_time','filtered_ac-
tual_time','filtered_osrm_time',actual_time,osrm_time,fil_actual_time,
fil_osrm_time)

```

Normality check - Histplot & QQ(prob)plot



```

col_names=
['clipped_actual_time','clipped_osrm_time','filtered_actual_time','filtered_osrm_time']
cols = [actual_time,osrm_time,fil_actual_time,fil_osrm_time]

for _ in zip(col_names,cols):
    normality = Normality_check(_[0],_[1])
    normality.shapiro_and_anderson()
    normality.boxcox_transformation()

```

Performing SHAPIRO & ANDERSON-DARLING TEST for `clipped_actual_time` column

`Shapiro-Wilk Test`
`clipped_actual_time - Data is not Gaussian`

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
`clipped_actual_time - Data does not follow a normal distribution.`

Performing BOXCOX transformation on `clipped_actual_time` column
 Performing SHAPIRO & ANDERSON-DARLING TEST for `clipped_actual_time` column

`Shapiro-Wilk Test`
`clipped_actual_time - Data is not Gaussian`

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test

```
clipped_actual_time - Data does not follow a normal distribution.
```

```
-----  
Performing SHAPIRO & ANDERSON-DARLING TEST for clipped_osrm_time  
column
```

```
Shapiro-Wilk Test  
clipped_osrm_time - Data is not Gaussian
```

```
Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test  
clipped_osrm_time - Data does not follow a normal distribution.
```

```
-----  
Performing BOXCOX transformation on clipped_osrm_time column  
Performing SHAPIRO & ANDERSON-DARLING TEST for clipped_osrm_time  
column
```

```
Shapiro-Wilk Test  
clipped_osrm_time - Data is not Gaussian
```

```
Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test  
clipped_osrm_time - Data does not follow a normal distribution.
```

```
-----  
Performing SHAPIRO & ANDERSON-DARLING TEST for filtered_actual_time  
column
```

```
Shapiro-Wilk Test  
filtered_actual_time - Data is not Gaussian
```

```
Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test  
filtered_actual_time - Data does not follow a normal distribution.
```

```
-----  
Performing BOXCOX transformation on filtered_actual_time column  
Performing SHAPIRO & ANDERSON-DARLING TEST for filtered_actual_time  
column
```

```
Shapiro-Wilk Test  
filtered_actual_time - Data is not Gaussian
```

```
Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test  
filtered_actual_time - Data does not follow a normal distribution.
```

```
-----  
Performing SHAPIRO & ANDERSON-DARLING TEST for filtered_osrm_time  
column
```

```
Shapiro-Wilk Test  
filtered_osrm_time - Data is not Gaussian
```

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
filtered_osrm_time - Data does not follow a normal distribution.

Performing BOXCox transformation on filtered_osrm_time column
Performing SHAPIRO & ANDERSON-DARLING TEST for filtered_osrm_time
column

Shapiro-Wilk Test
filtered_osrm_time - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
filtered_osrm_time - Data does not follow a normal distribution.

levene_test('clipped_actual_time','clipped_osrm_time',actual_time,osrm_time),
levene_test('filtered_actual_time','filtered_osrm_time',fil_actual_time,fil_osrm_time)

Performing Levene Test for clipped_actual_time & clipped_osrm_time
Does not have Homogenous (different) Variance

Performing Levene Test for filtered_actual_time & filtered_osrm_time
Does not have Homogenous (different) Variance

..

Wilcoxon signed rank test:

```
## with clipped data

# H0 : aggregated actual time is same as aggregated osrm time
# Ha : aggregated actual time is more than the aggregated osrm time

alpha = 0.05 #testing at 95% confidence

test_stat , p_value =
wilcoxon(actual_time,osrm_time,alternative='greater')

if p_value < alpha:
    print("Reject Null Hypothesis - The Aggregated Actual_time is More
than the Aggregated OSRM_time")
else:
```

```

    print("Fail to Reject Null Hypothesis - The Aggregated Actual_time
is same as the Aggregated OSRM_time")

Reject Null Hypothesis - The Aggregated Actual_time is More than the
Aggregated OSRM_time

## with filtered data

alpha = 0.05 #testing at 95% confidence

test_stat , p_value =
wilcoxon(fil_actual_time,fil_osrm_time,alternative='greater')

if p_value < alpha:
    print("Reject Null Hypothesis - The Aggregated Actual_time is More
than the Aggregated OSRM_time")
else:
    print("Fail to Reject Null Hypothesis - The Aggregated Actual_time
is same as the Aggregated OSRM_time")

Reject Null Hypothesis - The Aggregated Actual_time is More than the
Aggregated OSRM_time

### MannWhitney u Rank test

test_cols =
[('clipped_actual_time','clipped_osrm_time',actual_time,osrm_time),
 ('filtered_actual_time','filtered_osrm_time',fil_actual_time,fil_osrm_
time)]

for _ in test_cols:
    mannwhitneyu_test(_[0],_[1],_[2],_[3])

Performing Non-parametric Test - MannWhitneyU for clipped_actual_time
& clipped_osrm_time
Reject Null Hypothesis
There is a significant difference in the Mean values of
clipped_actual_time and clipped_osrm_time

-----
Performing Non-parametric Test - MannWhitneyU for filtered_actual_time
& filtered_osrm_time
Reject Null Hypothesis
There is a significant difference in the Mean values of
filtered_actual_time and filtered_osrm_time
-----
```

Insights:

It is confirmed that There is a significant difference in the Mean values of Aggregated actual_time and Aggregated osrm_time through **MannwhitneyU**test.

- $H_0: \mu_{\text{Aggregated-actual-time}} = \mu_{\text{Aggregated-osrm-time}}$

Further, it is found that The Aggregated Actual_time is More than the Aggregated OSRM_time through **Wilcoxon signed Rank** test.

- $H_0: \mu_{\text{Aggregated-actual-time}} > \mu_{\text{Aggregated-osrm-time}}$
-

Actual_time aggregated value and Segment actual time aggregated value.

```
clipped_num_df.sample()

    od_time_diff_hour  start_scan_to_end_scan \
11839          4.644768           278.0

    actual_distance_to_destination  actual_time  osrm_time
osrm_distance \
11839                  46.165558        104.0        63.0
75.968498

    segment_actual_time  segment_osrm_time
segment_osrm_distance \
11839            101.0             61.0           62.8657

    segment_actual_time_sum  segment_osrm_time_sum \
11839            101.0             61.0

    segment_osrm_distance_sum
11839            62.8657

clipped_num_df[['actual_time', 'segment_actual_time']].describe().T

                count      mean       std   min    25%    50%
75% \
actual_time      14787.0  224.212577  185.922840  9.0  67.0  148.0
367.0
segment_actual_time  14787.0  222.904643  185.797003  9.0  66.0  147.0
364.0

                max
actual_time      543.285302
segment_actual_time  543.285302

filtered_num_df[['actual_time', 'segment_actual_time']].describe().T
```

```

    count      mean       std   min   25%   50%
75% \
actual_time      14787.0  356.306000  561.517761  9.0  67.0  148.0
367.0
segment_actual_time 14787.0  353.059174  556.364441  9.0  66.0  147.0
364.0

          max
actual_time      6265.0
segment_actual_time 6230.0

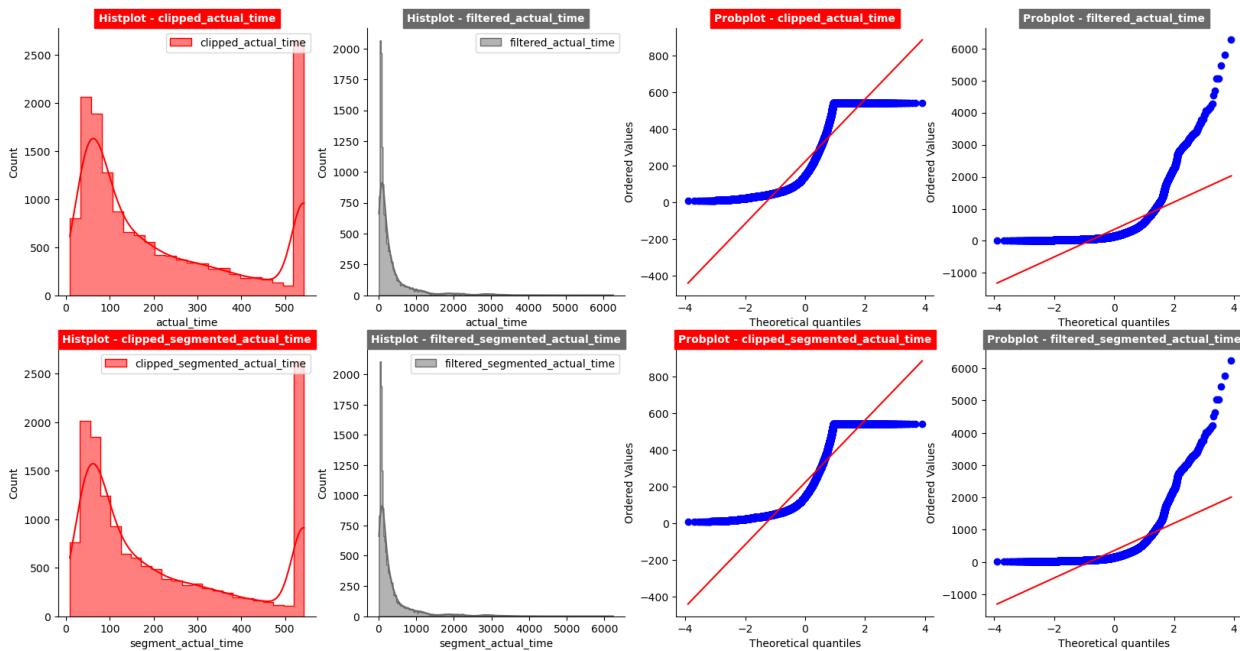
clipped_actual_time = clipped_num_df['actual_time']
clipped_segmented_actual_time = clipped_num_df['segment_actual_time']
filtered_actual_time = filtered_num_df['actual_time']
filtered_segmented_actual_time =
filtered_num_df['segment_actual_time']

normality_plots("clipped_actual_time","clipped_segmented_actual_time",
"filtered_actual_time","filtered_segmented_actual_time",

clipped_actual_time,clipped_segmented_actual_time,filtered_actual_time
,filtered_segmented_actual_time)

```

Normality check - Histplot & QQ(prob)plot



```

col_names=
["clipped_actual_time","clipped_segmented_actual_time","filtered_actua
l_time","filtered_segmented_actual_time"]
cols =
[clipped_actual_time,clipped_segmented_actual_time,filtered_actual_tim
e]

```

```
e,filtered_segmented_actual_time]

for _ in zip(col_names,cols):
    normality = Normality_check(_[0],_[1])
    normality.shapiro_and_anderson()
    normality.boxcox_transformation()

Performing SHAPIRO & ANDERSON-DARLING TEST for clipped_actual_time
column

Shapiro-Wilk Test
clipped_actual_time - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
clipped_actual_time - Data does not follow a normal distribution.

-----
Performing BOXCOX transformation on clipped_actual_time column
Performing SHAPIRO & ANDERSON-DARLING TEST for clipped_actual_time
column

Shapiro-Wilk Test
clipped_actual_time - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
clipped_actual_time - Data does not follow a normal distribution.

-----
Performing SHAPIRO & ANDERSON-DARLING TEST for
clipped_segmented_actual_time column

Shapiro-Wilk Test
clipped_segmented_actual_time - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
clipped_segmented_actual_time - Data does not follow a normal
distribution.

-----
Performing BOXCOX transformation on clipped_segmented_actual_time
column
Performing SHAPIRO & ANDERSON-DARLING TEST for
clipped_segmented_actual_time column

Shapiro-Wilk Test
clipped_segmented_actual_time - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
clipped_segmented_actual_time - Data does not follow a normal
distribution.
```

```
-----  
Performing SHAPIRO & ANDERSON-DARLING TEST for filtered_actual_time  
column
```

```
Shapiro-Wilk Test  
filtered_actual_time - Data is not Gaussian
```

```
Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test  
filtered_actual_time - Data does not follow a normal distribution.
```

```
-----  
Performing BOXCOX transformation on filtered_actual_time column  
Performing SHAPIRO & ANDERSON-DARLING TEST for filtered_actual_time  
column
```

```
Shapiro-Wilk Test  
filtered_actual_time - Data is not Gaussian
```

```
Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test  
filtered_actual_time - Data does not follow a normal distribution.
```

```
-----  
Performing SHAPIRO & ANDERSON-DARLING TEST for  
filtered_segmented_actual_time column
```

```
Shapiro-Wilk Test  
filtered_segmented_actual_time - Data is not Gaussian
```

```
Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test  
filtered_segmented_actual_time - Data does not follow a normal  
distribution.
```

```
-----  
Performing BOXCOX transformation on filtered_segmented_actual_time  
column
```

```
Performing SHAPIRO & ANDERSON-DARLING TEST for  
filtered_segmented_actual_time column
```

```
Shapiro-Wilk Test  
filtered_segmented_actual_time - Data is not Gaussian
```

```
Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test  
filtered_segmented_actual_time - Data does not follow a normal  
distribution.
```

```
-----  
levene_test("clipped_actual_time","clipped_segmented_actual_time",clip  
ped_actual_time,clipped_segmented_actual_time),  
levene_test("filtered_actual_time","filtered_segmented_actual_time",fi  
ltered_actual_time,filtered_segmented_actual_time)
```

```

Performing Levene Test for clipped_actual_time &
clipped_segmented_actual_time
Have Homogenous (similar) variance
-----
Performing Levene Test for filtered_actual_time &
filtered_segmented_actual_time
Have Homogenous (similar) variance
-----
"""

### MannWhitney u Rank test

test_cols =
[("clipped_actual_time","clipped_segmented_actual_time",clipped_actual_time,clipped_segmented_actual_time),
 ("filtered_actual_time","filtered_segmented_actual_time",filtered_actual_time,filtered_segmented_actual_time)]

for _ in test_cols:
    mannwhitneyu_test(_[0],_[1],_[2],_[3])

Performing Non-parametric Test - MannWhitneyU for clipped_actual_time
& clipped_segmented_actual_time
Failed to Reject Null Hypothesis - Accept H0
There is NO significant difference in the Mean values of
clipped_actual_time and clipped_segmented_actual_time
-----
Performing Non-parametric Test - MannWhitneyU for filtered_actual_time
& filtered_segmented_actual_time
Failed to Reject Null Hypothesis - Accept H0
There is NO significant difference in the Mean values of
filtered_actual_time and filtered_segmented_actual_time
-----
```

Insights:

Even though data is not gaussian , though it has similar variance (confirmed by **Levene's test**)

It is confirmed that There is NO significant difference in the Mean values of Aggregated actual_time and segmented_actual_time through **MannWhitneyU test**.

- $H_0: \mu_{\text{Aggregated-actual-time}} = \mu_{\text{Segmented-actual-time}}$

OSRM distance aggregated value and segment OSRM distance aggregated value.

```
filtered_num_df.sample()

3944    od_time_diff_hour  start_scan_to_end_scan  \
          5.694592                  341.0

           actual_distance_to_destination  actual_time  osrm_time
osrm_distance  \
3944              88.352287        156.0         71.0
101.823898

           segment_actual_time  segment_osrm_time  segment_osrm_distance  \
3944            155.0             70.0            101.823898

           segment_actual_time_sum  segment_osrm_time_sum  \
3944            155.0             70.0

           segment_osrm_distance_sum
3944            101.823898

clipped_num_df[['osrm_distance', 'segment_osrm_distance']].describe().T

           count      mean       std      min
25%  \
osrm_distance      14787.0  144.551531  162.880435  9.0729
30.75690
segment_osrm_distance  14787.0  150.959153  165.473080  9.0729
32.57885

           50%      75%      max
osrm_distance      65.302795  206.644203  543.285302
segment_osrm_distance  69.784203  216.560608  543.285302

filtered_num_df[['osrm_distance', 'segment_osrm_distance']].describe().T

           count      mean       std      min
25%  \
osrm_distance      14787.0  203.887405  370.565460  9.0729
30.75690
segment_osrm_distance  14787.0  222.705444  416.845642  9.0729
32.57885

           50%      75%      max
osrm_distance      65.302795  206.644203  2840.081055
segment_osrm_distance  69.784203  216.560608  3523.632324
```

```

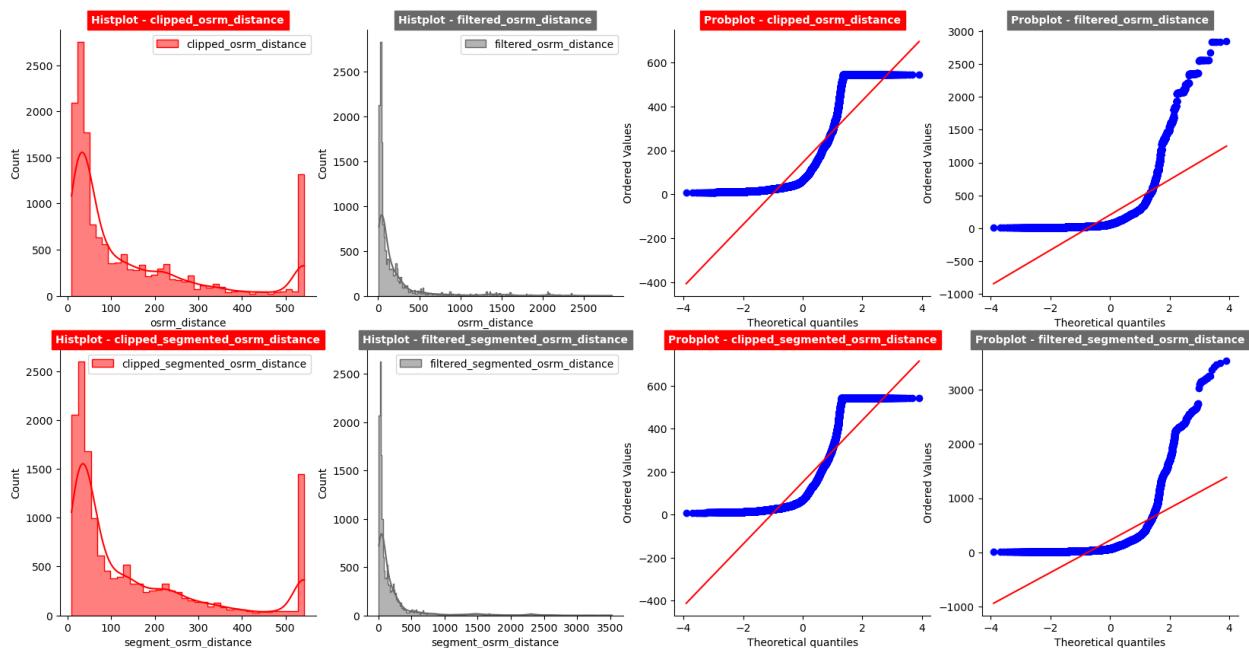
clipped_osrm_distance = clipped_num_df['osrm_distance']
clipped_segmented_osrm_distance =
clipped_num_df['segment_osrm_distance']
filtered_osrm_distance = filtered_num_df['osrm_distance']
filtered_segmented_osrm_distance =
filtered_num_df['segment_osrm_distance']

normality_plots("clipped_osrm_distance", "clipped_segmented_osrm_distan-
ce", "filtered_osrm_distance", "filtered_segmented_osrm_distance",

clipped_osrm_distance,clipped_segmented_osrm_distance,filtered_osrm_di-
stance,filtered_segmented_osrm_distance)

```

Normality check - Histplot & QQ(prob)plot



```

col_names=
["clipped_osrm_distance", "clipped_segmented_osrm_distance", "filtered_o-
srm_distance", "filtered_segmented_osrm_distance"]
cols =
[clipped_osrm_distance,clipped_segmented_osrm_distance,filtered_osrm_d-
istance,filtered_segmented_osrm_distance]

for _ in zip(col_names,cols):
    normality = Normality_check(_[0],_[1])
    normality.shapiro_and_anderson()
    normality.boxcox_transformation()

```

Performing SHAPIRO & ANDERSON-DARLING TEST for clipped_osrm_distance column

```
Shapiro-Wilk Test
clipped_osrm_distance - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
clipped_osrm_distance - Data does not follow a normal distribution.

-----
Performing BOXCOX transformation on clipped_osrm_distance column
Performing SHAPIRO & ANDERSON-DARLING TEST for clipped_osrm_distance
column

Shapiro-Wilk Test
clipped_osrm_distance - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
clipped_osrm_distance - Data does not follow a normal distribution.

-----
Performing SHAPIRO & ANDERSON-DARLING TEST for
clipped_segmented_osrm_distance column

Shapiro-Wilk Test
clipped_segmented_osrm_distance - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
clipped_segmented_osrm_distance - Data does not follow a normal
distribution.

-----
Performing BOXCOX transformation on clipped_segmented_osrm_distance
column
Performing SHAPIRO & ANDERSON-DARLING TEST for
clipped_segmented_osrm_distance column

Shapiro-Wilk Test
clipped_segmented_osrm_distance - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
clipped_segmented_osrm_distance - Data does not follow a normal
distribution.

-----
Performing SHAPIRO & ANDERSON-DARLING TEST for filtered_osrm_distance
column

Shapiro-Wilk Test
filtered_osrm_distance - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
filtered_osrm_distance - Data does not follow a normal distribution.
```

```
-----  
Performing BOXCOX transformation on filtered_osrm_distance column  
Performing SHAPIRO & ANDERSON-DARLING TEST for filtered_osrm_distance  
column
```

```
Shapiro-Wilk Test  
filtered_osrm_distance - Data is not Gaussian
```

```
Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test  
filtered_osrm_distance - Data does not follow a normal distribution.
```

```
-----  
Performing SHAPIRO & ANDERSON-DARLING TEST for  
filtered_segmented_osrm_distance column
```

```
Shapiro-Wilk Test  
filtered_segmented_osrm_distance - Data is not Gaussian
```

```
Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test  
filtered_segmented_osrm_distance - Data does not follow a normal  
distribution.
```

```
-----  
Performing BOXCOX transformation on filtered_segmented_osrm_distance  
column
```

```
Performing SHAPIRO & ANDERSON-DARLING TEST for  
filtered_segmented_osrm_distance column
```

```
Shapiro-Wilk Test  
filtered_segmented_osrm_distance - Data is not Gaussian
```

```
Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test  
filtered_segmented_osrm_distance - Data does not follow a normal  
distribution.
```

```
-----  
levene_test("clipped_osrm_distance","clipped_segmented_osrm_distance",  
clipped_osrm_distance,clipped_segmented_osrm_distance),  
levene_test("filtered_osrm_distance","filtered_segmented_osrm_distance",  
" ,filtered_osrm_distance,filtered_segmented_osrm_distance)
```

```
Performing Levene Test for clipped_osrm_distance &  
clipped_segmented_osrm_distance  
Does not have Homogenous (different) Variance
```

```
-----  
Performing Levene Test for filtered_osrm_distance &  
filtered_segmented_osrm_distance  
Does not have Homogenous (different) Variance
```

```

''

### MannWhitney u Rank test

test_cols =
[("clipped_osrm_distance","clipped_segmented_osrm_distance",clipped_osrm_distance,clipped_segmented_osrm_distance),
 ("filtered_osrm_distance","filtered_segmented_osrm_distance",filtered_osrm_distance,filtered_segmented_osrm_distance)]

for _ in test_cols:
    mannwhitneyu_test(_[0],_[1],_[2],_[3])

Performing Non-parametric Test - MannWhitneyU for
clipped_osrm_distance & clipped_segmented_osrm_distance
Reject Null Hypothesis
There is a significant difference in the Mean values of
clipped_osrm_distance and clipped_segmented_osrm_distance

-----
Performing Non-parametric Test - MannWhitneyU for
filtered_osrm_distance & filtered_segmented_osrm_distance
Reject Null Hypothesis
There is a significant difference in the Mean values of
filtered_osrm_distance and filtered_segmented_osrm_distance
-----
```

Insights:

It is confirmed that There is a significant difference in the Mean values of osrm_distance and segmented_osrm_distance aggregated through **MannwhitneyU**test.

- $H_0: \mu_{\text{Aggregated-osrm-distance}} \neq \mu_{\text{Segmented-osrm-distance-aggregated}}$

OSRM time aggregated value and segment OSRM time aggregated value.

```
filtered_num_df.sample()

   od_time_diff_hour  start_scan_to_end_scan  \
113           3.763914            225.0
```

```

    actual_distance_to_destination  actual_time  osrm_time
osrm_distance \
113                      45.959438        140.0       57.0
54.921398

    segment_actual_time  segment_osrm_time  segment_osrm_distance \
113                  138.0            66.0          64.504799

    segment_actual_time_sum  segment_osrm_time_sum
segment_osrm_distance_sum
113                      138.0            66.0
64.504799

clipped_num_df[['osrm_time','segment_osrm_time']].describe().T

              count      mean       std   min   25%   50%
75% \
osrm_time      14787.0  128.190912  150.301267  6.0  29.0  60.0
168.0
segment_osrm_time  14787.0  136.843818  155.422255  6.0  30.0  65.0
184.0

              max
osrm_time      543.285302
segment_osrm_time  543.285302

filtered_num_df[['osrm_time','segment_osrm_time']].describe().T

              count      mean       std   min   25%   50%
75% \
osrm_time      14787.0  160.990936  271.459229  6.0  29.0  60.0
168.0
segment_osrm_time  14787.0  180.511597  314.678741  6.0  30.0  65.0
184.0

              max
osrm_time      2032.0
segment_osrm_time  2564.0

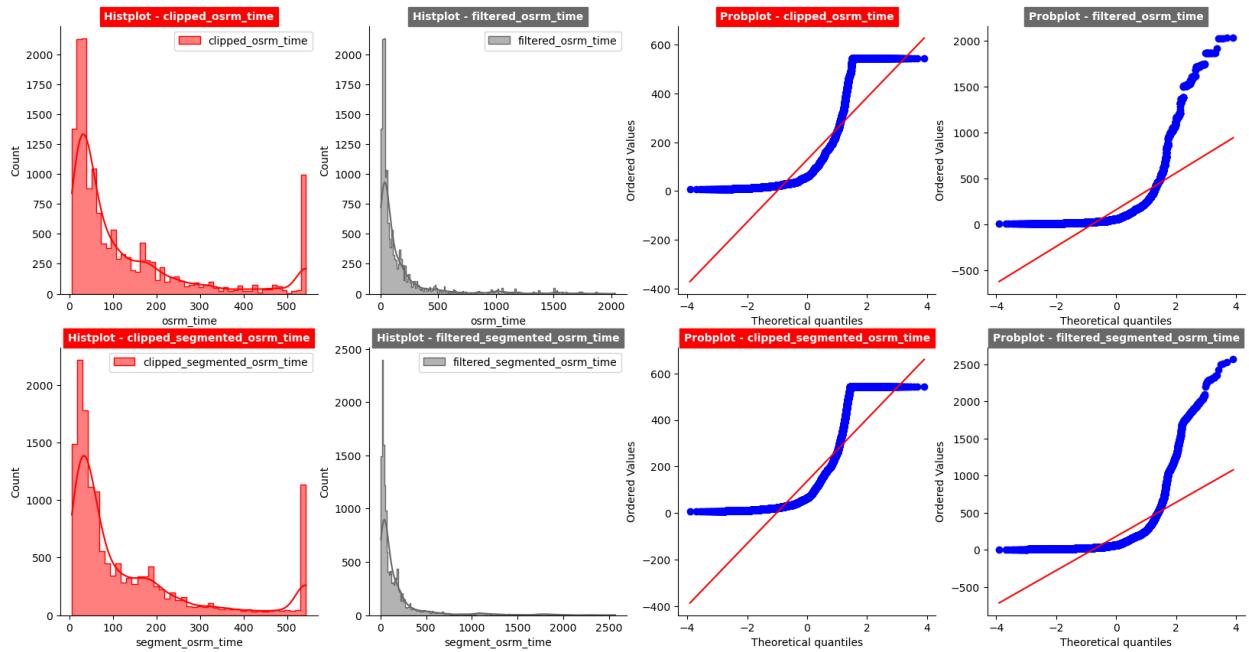
clipped_osrm_time = clipped_num_df['osrm_time']
clipped_segmented_osrm_time = clipped_num_df['segment_osrm_time']
filtered_osrm_time = filtered_num_df['osrm_time']
filtered_segmented_osrm_time = filtered_num_df['segment_osrm_time']

normality_plots("clipped_osrm_time","clipped_segmented_osrm_time","fil
tered_osrm_time","filtered_segmented_osrm_time",

clipped_osrm_time,clipped_segmented_osrm_time,filtered_osrm_time,filte
red_segmented_osrm_time)

```

Normality check - Histplot & QQ(prob)plot



```

col_names=
["clipped_osrm_time", "clipped_segmented_osrm_time", "filtered_osrm_time",
 "filtered_segmented_osrm_time"]
cols =
[clipped_osrm_time, clipped_segmented_osrm_time, filtered_osrm_time, filtered_segmented_osrm_time]

for _ in zip(col_names,cols):
    normality = Normality_check(_[0],_[1])
    normality.shapiro_and_anderson()
    normality.boxcox_transformation()

```

Performing SHAPIRO & ANDERSON-DARLING TEST for `clipped_osrm_time` column

Shapiro-Wilk Test
`clipped_osrm_time` - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
`clipped_osrm_time` - Data does not follow a normal distribution.

Performing BOXCOX transformation on `clipped_osrm_time` column
Performing SHAPIRO & ANDERSON-DARLING TEST for `clipped_osrm_time` column

Shapiro-Wilk Test
`clipped_osrm_time` - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
clipped_osrm_time - Data does not follow a normal distribution.

Performing SHAPIRO & ANDERSON-DARLING TEST for
clipped_segmented_osrm_time column

Shapiro-Wilk Test
clipped_segmented_osrm_time - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
clipped_segmented_osrm_time - Data does not follow a normal
distribution.

Performing BOXCOX transformation on clipped_segmented_osrm_time column
Performing SHAPIRO & ANDERSON-DARLING TEST for
clipped_segmented_osrm_time column

Shapiro-Wilk Test
clipped_segmented_osrm_time - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
clipped_segmented_osrm_time - Data does not follow a normal
distribution.

Performing SHAPIRO & ANDERSON-DARLING TEST for filtered_osrm_time
column

Shapiro-Wilk Test
filtered_osrm_time - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
filtered_osrm_time - Data does not follow a normal distribution.

Performing BOXCOX transformation on filtered_osrm_time column
Performing SHAPIRO & ANDERSON-DARLING TEST for filtered_osrm_time
column

Shapiro-Wilk Test
filtered_osrm_time - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
filtered_osrm_time - Data does not follow a normal distribution.

Performing SHAPIRO & ANDERSON-DARLING TEST for
filtered_segmented_osrm_time column

```
Shapiro-Wilk Test
filtered_segmented_osrm_time - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
filtered_segmented_osrm_time - Data does not follow a normal
distribution.

-----
Performing BOXCOX transformation on filtered_segmented_osrm_time
column
Performing SHAPIRO & ANDERSON-DARLING TEST for
filtered_segmented_osrm_time column

Shapiro-Wilk Test
filtered_segmented_osrm_time - Data is not Gaussian

Since Shapiro-Wilk test is sensitive, we go with Anderson-Darling Test
filtered_segmented_osrm_time - Data does not follow a normal
distribution.

-----
levene_test("clipped_osrm_time","clipped_segmented_osrm_time",clipped_
osrm_time,clipped_segmented_osrm_time),
levene_test("filtered_osrm_time","filtered_segmented_osrm_time",filter
ed_osrm_time,filtered_segmented_osrm_time)

Performing Levene Test for clipped_osrm_time &
clipped_segmented_osrm_time
Does not have Homogenous (different) Variance

-----
Performing Levene Test for filtered_osrm_time &
filtered_segmented_osrm_time
Does not have Homogenous (different) Variance

-----
```
MannWhitney u Rank test

test_cols =
[("clipped_osrm_time","clipped_segmented_osrm_time",clipped_osrm_time,
clipped_segmented_osrm_time),
 ("filtered_osrm_time","filtered_segmented_osrm_time",filtered_osrm_time,
filtered_segmented_osrm_time)]
```

```

for _ in test_cols:
 mannwhitneyu_test(_[0],_[1],_[2],_[3])

Performing Non-parametric Test - MannWhitneyU for clipped_osrm_time &
clipped_segmented_osrm_time
Reject Null Hypothesis
There is a significant difference in the Mean values of
clipped_osrm_time and clipped_segmented_osrm_time

Performing Non-parametric Test - MannWhitneyU for filtered_osrm_time &
filtered_segmented_osrm_time
Reject Null Hypothesis
There is a significant difference in the Mean values of
filtered_osrm_time and filtered_segmented_osrm_time

```

Insights:

It is confirmed that There is a significant difference in the Mean values of Aggregated osrm\_time and segmented\_osrm\_time aggregated through *MannwhitneyU*test.

- $H_0: \mu_{\text{Aggregated-osrm-time}} = \mu_{\text{Segmented-osrm-time-aggregated}}$

```

trip_df.sample()

 trip_uuid data route_type
od_start_time \
8533 trip-153774183943645102 training Carting 2018-09-24
00:46:07.807847

 od_end_time od_time_diff_hour
trip_creation_time \
8533 2018-09-24 07:32:00.833381 9.02261 2018-09-23
22:30:39.436721

 trip_creation_month trip_creation_year trip_creation_day \
8533 9 2018 23

 trip_creation_hour trip_creation_weekday trip_creation_week \
8533 22 6 38

 start_scan_to_end_scan actual_distance_to_destination
actual_time \
8533 540.0 110.157166
```

```

268.0

 osrm_time osrm_distance segment_actual_time segment_osrm_time
\ 8533 132.0 168.731094 265.0 153.0

 segment_osrm_distance segment_actual_time_sum
segment_osrm_time_sum \
8533 195.579712 265.0
153.0

 segment_osrm_distance_sum source_name
source_city \
8533 195.579712 Bagnan_Harop_D (West Bengal)
Bagnan

 source_state source_place
destination_name \
8533 West Bengal Harop_D Kolaghat_Central_DPP_2 (West Bengal)

 destination_city destination_state destination_place \
8533 Kolaghat West Bengal Central_DPP_2

 corridor \
8533 Bagnan_Harop_D (West Bengal) <---> Kolaghat_Ce...

 state_corridor \
8533 West Bengal--Bagnan <---> West Bengal--Kolaghat

 city_corridor
trip_creation_day_week \
8533 Bagnan--Harop_D <---> Kolaghat--Central_DPP_2
Sunday

 trip_creation_dayofdate
8533 23

To find the busiest corridor, we'll look at the most common combinations of source and destination states
corridor_counts = trip_df.groupby(['source_state',
'destination_state']).size().reset_index(name='count')
busiest_corridor = corridor_counts.sort_values(by='count',
ascending=False).head(1)

Average distance and time taken for the busiest corridor
busiest_corridor_details = busiest_corridor.merge(trip_df,
on=['source_state', 'destination_state'])
average_distance =
busiest_corridor_details['actual_distance_to_destination'].mean()

```

```

average_time = busiest_corridor_details['od_time_diff_hour'].mean()

print("Busiest corridor: ")
display(busiest_corridor)
print("Average distance: ", average_distance)
print("Average time (in hours): ", average_time)

Busiest corridor:

 source_state destination_state count
85 Maharashtra Maharashtra 2458

Average distance: 74.852844
Average time (in hours): 5.346577921457034

```

## Buisness Insights

### Based on EDA:

- The Timeframe of the data is '2018-09-12' to '2018-10-08' i.e(26 days).
- 88% of the trips are from October Month & remaining are from November
- The entire data is heavily right skewed
- Almost all the features are heavily positively correlated with each other & which is intuitive as well.
- Start & End dates of the months have less percent of trips compare to mid of the month. Though the difference is not huge
- That's very strange to see that there is absolutely no trip from 4th- 11th day of the month
- Most orders come mid-month. That means customers usually make more orders in the mid of the month.

### Route type:

- The analysis reveals that a higher proportion of shipments are routed through Full Truck Load (FTL) as opposed to carting. This has important implications for the efficiency and speed of the delivery process.

### Geographical Focus:

Understanding the busiest routes and distances can help in optimizing logistics operations, improving transportation efficiency, and potentially reducing costs.

- **State:** The states of Haryana, Maharashtra, and Karnataka are not only busy source states but also emerge as the busiest source states, indicating a high demand or significant business activities originating from these regions.
- **source city:** Gurgaon, Bangalore, and Bhiwandi are identified as the busiest source cities, suggesting that these cities play a crucial role in contributing to the overall business operations or transportation activities.

- **Destination city:** Gurgaon, Bangalore, and Hyderabad are identified as the busiest destination cities, underscoring their significance in terms of business activities or population movement.
- **Busiest corridor:** Overall, the busiest corridor is Mumbai\_Maharashtra and Bangalore\_Karnataka which has the maximum trips.
  - Average distance: 74.852844 kms
  - Average time (in hours): 5.346577921457034

### **Delivery Time & Distance Accuracy:**

#### **OSRM Time vs. Actual Time:**

- The difference between the mean values of estimated delivery time and actual delivery time suggests that there may be variations or delays in the actual delivery process compared to the initial estimates.
- The fact that the mean of OSRM time is less than the mean of actual delivery time indicates that the estimated times provided by the OSRM (Open Source Routing Machine) service tend to be optimistic.

#### **OSRM Distance vs. Actual Distance:**

- The mean of OSRM distance being greater than the mean of actual distance to the destination suggests that the OSRM might overestimate the distances. This could impact route planning and fuel efficiency calculations.

#### **Segment-wise time Analysis:**

- The equality in the mean values of actual time and segment actual time suggests that the time measurements are consistent across different segments of the delivery process

#### **Segment-wise distance Analysis:**

- The mean of segment OSRM distance being greater than the mean of OSRM distance implies that the OSRM might provide more conservative estimates for distance within individual segments.

#### **Further look into :**

- As its depicted from the analysis that there is absolutely no trip from 4th- 11th day of the month, The reason for that can be figured out and catered to receive the orders in the these dates as well.
  - More ways to promote FTL route handling system can be implemented to increase this percentage
- 

## **Business Recommendations**

### **Route Optimization:**

- Given that the busiest state route is within Karnataka, it might be beneficial to optimize the transportation network within Karnataka to improve efficiency and reduce congestion. Consider implementing route optimization algorithms and real-time traffic monitoring to enhance the transportation system.
- Since Gurgaon and Bangalore are identified as the busiest source and destination cities, respectively, focus on city-specific strategies to manage the high traffic volume.

#### **Operational Efficiency:**

- Since mean of OSRM time is less than the mean of actual delivery time, Businesses could use this insight to set more realistic delivery time expectations for customers.
- Since the mean of OSRM distance greater than the mean of actual distance, Businesses should consider adjusting their distance estimations for more accurate logistics planning.
- Since the mean of segment OSRM distance greater than the mean of OSRM distance, along with this, we have the actual distance travelled, Businesses can use this information to fine-tune their route planning and optimize segment-specific logistics.
- Implement advanced demand forecasting techniques to anticipate peak travel times and adjust transportation services accordingly. This proactive approach can help in better resource allocation and minimize the impact of congestion during peak hours.
- Overall, the analysis hints at potential areas for operational improvement. Businesses could focus on refining their route planning algorithms, addressing discrepancies in estimated times and distances, and streamlining processes between different stages of delivery to enhance overall operational efficiency.

#### **Customer Satisfaction:**

- Improving accuracy in estimated delivery times and distances can contribute to increased customer satisfaction.
- FTL shipments: Faster delivery times, facilitated by a higher proportion of FTL shipments, can directly impact customer satisfaction. Customers typically value timely deliveries, and this strategic choice aligns with meeting or exceeding customer expectations in terms of shipment speed.

#### **Customer profiling:**

- Customer profiling of the customers belonging to the states Maharashtra, Karnataka, Haryana, Tamil Nadu and Uttar Pradesh has to be done to get to know why major orders are coming from these states and to improve customers' buying and delivery experience.

#### **Cost Optimization:**

- Understanding the differences in estimated and actual times and distances can aid in cost optimization efforts.
- Fine-tuning logistics planning based on more accurate measurements can lead to better resource allocation and potentially reduce operational costs.

#### **Strategic Decision-making:**

- The preference for FTL over carting reflects a strategic decision by the logistics management.
- Understanding the reasons behind this choice and continuously evaluating its impact can guide future decision-making processes and help adapt to evolving business needs.

**Collaboration with Stakeholders:**

- Collaborate with relevant stakeholders, including government authorities, transportation companies, and local communities, to develop and implement comprehensive strategies for managing and optimizing transportation in the identified busy corridors and cities.