🚚 DELHIVERY - Business CaseStudy 🚚

Feature Engineering

Analysed by : **KASI**

![Delhivery-Success-story-startuptalky1.jpg](attachment:edaa1eb4-32bc-4ce8-a3d4-67ab6a015f9c.jpg) ![image-asset.gif](attachment:a565dc86-3065-4af7-830f-5044490f3034.gif)

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.

Usecase:

- 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.
  - Itprovides 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.
  - Byconducting 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 subset of the package delivery
segment_osrm_distance	This is the OSRM distance. Distance covered by subset of the package delivery
segment_factor	Unknown field

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

In [1]:
```
# 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')
```

In [2]:
```
# pd_reading the data
delhivery_data = pd.read_csv('delhivery_data.csv')
```

In [3]:
```
# setting the option of displaying all the columns
pd.set_option('display.max_columns', 50)
```

In [4]:
```
# making a deep copy for backup
dd = delhivery_data.copy()
dd.head()
```

Out[4]:

	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
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	86.0	True
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	86.0	True
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	86.0	True
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	86.0	True
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khambhat_MotvdDPP_D (Gujarat)	2018-09-20 03:21:32.418600	2018-09-20 04:47:45.236797	86.0	False

🧐 Exploration of data :

In [5]:
```
dd.shape
```

Out[5]:
```
(144867, 24)
```

In [6]:
```
dd.columns
```

Out[6]:
```
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')
```

In [7]:
```
dd.info()
```

Out[7]:
```
<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

In [8]:
```
dd.describe().T
```

Out[8]:

	count	mean	std	min	25%	50%	75%	max
start_scan_to_end_scan	144867.0	961.262986	1037.012769	20.000000	161.000000	449.000000	1634.000000	7898.000000
cutoff_factor	144867.0	232.926567	344.755577	9.000000	22.000000	66.000000	286.000000	1927.000000
actual_distance_to_destination	144867.0	234.073372	344.990009	9.000045	23.355874	66.126571	286.708875	1927.447705
actual_time	144867.0	416.927527	598.103621	9.000000	51.000000	132.000000	513.000000	4532.000000
osrm_time	144867.0	213.868272	308.011085	6.000000	27.000000	64.000000	257.000000	1686.000000
osrm_distance	144867.0	284.771297	421.119294	9.008200	29.914700	78.525800	343.193250	2326.199100
factor	144867.0	2.120107	1.715421	0.144000	1.604264	1.857143	2.213483	77.387097
segment_actual_time	144867.0	36.196111	53.571158	-244.000000	20.000000	29.000000	40.000000	3051.000000
segment_osrm_time	144867.0	18.507548	14.775960	0.000000	11.000000	17.000000	22.000000	1611.000000
segment_osrm_distance	144867.0	22.829020	17.860660	0.000000	12.070100	23.513000	27.813250	2191.403700
segment_factor	144867.0	2.218368	4.847530	-23.444444	1.347826	1.684211	2.250000	574.250000

In [9]:
```
dd.describe(include=object).T
```

Out[9]:

	count	unique	top	freq
data	144867	2	training	104858
trip_creation_time	144867	14817	2018-09-28 05:23:15.359220	101
route_schedule_uuid	144867	1504	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	1812
route_type	144867	2	FTL	99660
trip_uuid	144867	14817	trip-153811219535896559	101
source_center	144867	1508	IND000000ACB	23347
source_name	144574	1498	Gurgaon_Bilaspur_HB (Haryana)	23347
destination_center	144867	1481	IND000000ACB	15192
destination_name	144606	1468	Gurgaon_Bilaspur_HB (Haryana)	15192
od_start_time	144867	26369	2018-09-21 18:37:09.322207	81
od_end_time	144867	26369	2018-09-24 09:59:15.691618	81
cutoff_timestamp	144867	93180	2018-09-24 05:19:20	40

📜 📜 Duplicate Detection

In [10]:
```
dd[dd.duplicated()]
```

Out[10]:

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

🏷️ Insights

- The dataset does not contain any duplicates.

🔸 ❓ Null Detection

In [11]:
```
dd.isna().any()
```

Out[11]:
```
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
```

In [12]:
```
dd.isnull().sum()
```

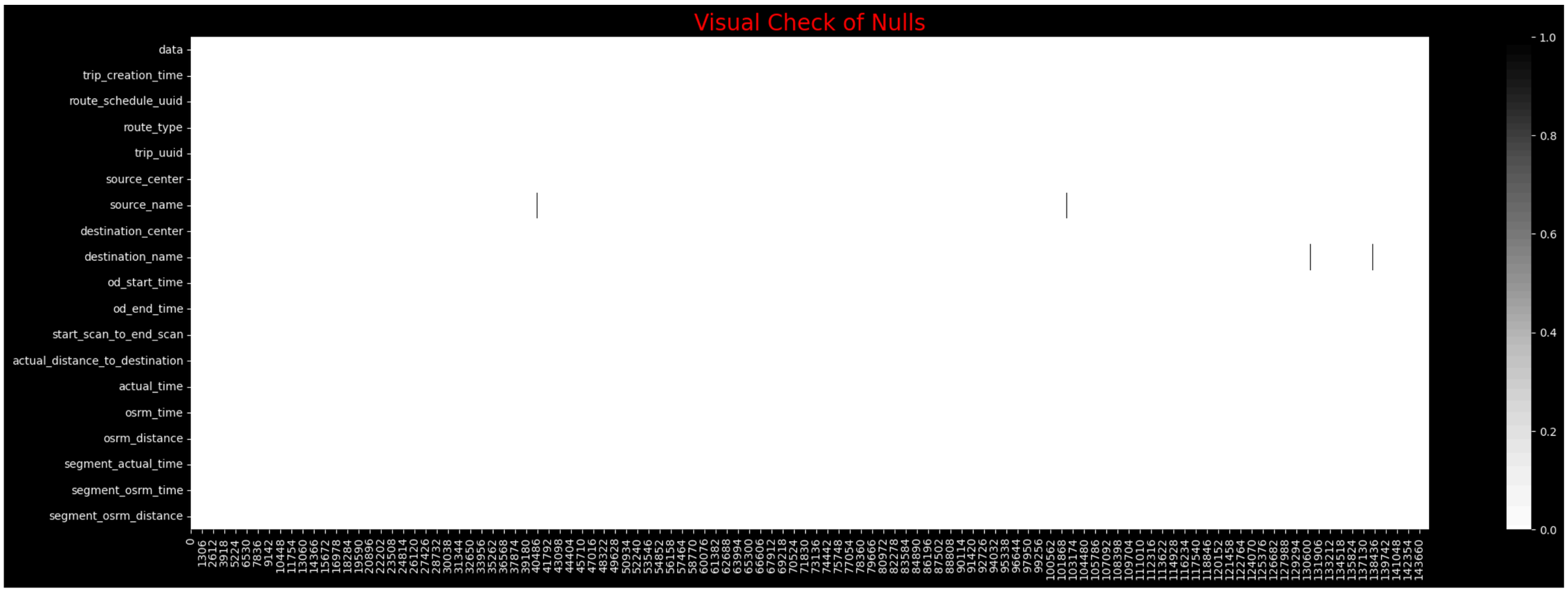
Out[12]:
```
data                              0
trip_creation_time                0
route_schedule_uuid               0
route_type                        0
trip_uuid                         0
source_center                     0
source_name                     293
destination_center                0
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
```

In [13]:
```
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]
```

Out[13]:

	Total	Percent
source_name	293	0.202254
destination_name	261	0.180165

In [16]:
```
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()
```



In [15]:
```
# Dropping unknown fields

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

In [17]:
```
dd.sample()
```

Out[17]:

	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	actua
133488	test	2018-09-30 05:56:48.299467	thanos::sroute:6be6529b-f2ad-4714-b7ab-ac58f24...	FTL	trip-153828700829921150	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)	IND600056AAB	MAA_Poonamallee_HB (Tamil Nadu)	2018-09-30 05:56:48.299467	2018-10-02 10:36:25.970169	3159.0	

In [18]:
```
dd.shape
```

Out[18]:
```
(144867, 19)
```

In [19]:
```
#checking the unique values for columns
for _ in dd.columns:
    print()
    print(f'Total Unique Values in {_} column are :- {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

In [20]:
```
dd.sample()
```

Out[20]:

	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	actual_
124444	training	2018-09-23 02:44:13.665024	thanos::sroute:f01c8bbd-655d-42ea-9abf-60d5040...	FTL	trip-153767065366477819	IND821115AAB	Sasaram_Central_I_2 (Bihar)	IND209304AAA	Kanpur_Central_H_6 (Uttar Pradesh)	2018-09-23 17:32:37.941229	2018-09-24 04:42:20.756776	669.0	

In [21]:
```
dd.dtypes
```

Out[21]:
```
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
```

In [22]:
```
# 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[_])
```

In [23]:
```
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

In [24]:
```
float_cols = []
for _ in dd.columns:
    if dd[_].dtype=='float64':
        float_cols.append(_)
float_cols
```

Out[24]:
```
['start_scan_to_end_scan',
 'actual_distance_to_destination',
 'actual_time',
 'osrm_time',
 'osrm_distance',
 'segment_actual_time',
 'segment_osrm_time',
 'segment_osrm_distance']
```

In [25]:
```
# reducing the float64 to float32 to save memory
for _ in float_cols:
    dd[_] = dd[_].astype('float32')
```

In [26]:
```
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  float32
 12  actual_distance_to_destination  144867 non-null  float32
 13  actual_time                     144867 non-null  float32
 14  osrm_time                       144867 non-null  float32
 15  osrm_distance                   144867 non-null  float32
 16  segment_actual_time             144867 non-null  float32
 17  segment_osrm_time               144867 non-null  float32
 18  segment_osrm_distance           144867 non-null  float32
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.

In [27]:
```
# Time period of data
dd['trip_creation_time'].max(), dd['trip_creation_time'].min() , dd['trip_creation_time'].max()-dd['trip_creation_time'].min()
```

Out[27]:
```
(Timestamp('2018-10-03 23:59:42.701692'),
 Timestamp('2018-09-12 00:00:16.535741'),
 Timedelta('21 days 23:59:26.165951'))
```

In [28]:
```
# Time period of data
dd['od_start_time'].max(), dd['od_start_time'].min(), dd['od_start_time'].max() - dd['od_start_time'].min()
```

Out[28]:
```
(Timestamp('2018-10-06 04:27:23.392375'),
 Timestamp('2018-09-12 00:00:16.535741'),
 Timedelta('24 days 04:27:06.856634'))
```

In [29]:
```
# Time period of data
dd['od_end_time'].max(), dd['od_end_time'].min(), dd['od_end_time'].max() - dd['od_end_time'].min()
```

Out[29]:
```
(Timestamp('2018-10-08 03:00:24.353479'),
 Timestamp('2018-09-12 00:50:10.814399'),
 Timedelta('26 days 02:10:13.539080'))
```

In [30]:
```
data_time_frame =  dd['od_end_time'].max() - dd['trip_creation_time'].min()
data_time_frame
```

Out[30]:
```
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` ....

In [31]:
```
dd[(dd.source_name.isna())&(dd.destination_name.isna())]
```

Out[31]:

	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	actual_distance
68006	training	2018-09-26 22:21:56.619259	thanos::sroute:cfb575b8-df26-48f5-8427-6f48f9d...	FTL	trip-153800051661903546	IND331022A1B	NaN	IND331001A1C	NaN	2018-09-27 03:19:14.797080	2018-09-27 05:28:00.922915	128.0	
68007	training	2018-09-26 22:21:56.619259	thanos::sroute:cfb575b8-df26-48f5-8427-6f48f9d...	FTL	trip-153800051661903546	IND331022A1B	NaN	IND331001A1C	NaN	2018-09-27 03:19:14.797080	2018-09-27 05:28:00.922915	128.0	
68008	training	2018-09-26 22:21:56.619259	thanos::sroute:cfb575b8-df26-48f5-8427-6f48f9d...	FTL	trip-153800051661903546	IND331022A1B	NaN	IND331001A1C	NaN	2018-09-27 03:19:14.797080	2018-09-27 05:28:00.922915	128.0	

In [32]:
```
dd[dd.source_name.isna()]
```

Out[32]:

	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	actual_distan
112	training	2018-09-25 08:53:04.377810	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	trip-153786558437756691	IND342902A1B	NaN	IND302014AAA	Jaipur_Hub (Rajasthan)	2018-09-26 06:58:08.054001	2018-09-26 15:54:14.280942	536.0	
113	training	2018-09-25 08:53:04.377810	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	trip-153786558437756691	IND342902A1B	NaN	IND302014AAA	Jaipur_Hub (Rajasthan)	2018-09-26 06:58:08.054001	2018-09-26 15:54:14.280942	536.0	
114	training	2018-09-25 08:53:04.377810	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	trip-153786558437756691	IND342902A1B	NaN	IND302014AAA	Jaipur_Hub (Rajasthan)	2018-09-26 06:58:08.054001	2018-09-26 15:54:14.280942	536.0	
115	training	2018-09-25 08:53:04.377810	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	trip-153786558437756691	IND342902A1B	NaN	IND302014AAA	Jaipur_Hub (Rajasthan)	2018-09-26 06:58:08.054001	2018-09-26 15:54:14.280942	536.0	
116	training	2018-09-25 08:53:04.377810	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	trip-153786558437756691	IND342902A1B	NaN	IND302014AAA	Jaipur_Hub (Rajasthan)	2018-09-26 06:58:08.054001	2018-09-26 15:54:14.280942	536.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
144484	test	2018-10-03 09:06:06.690094	thanos::sroute:cbef3b6a-79ea-4d5e-a215-b558a70...	FTL	trip-153855756668984584	IND282002AAD	NaN	IND474003AAA	Gwalior_HrihrNgr_I (Madhya Pradesh)	2018-10-03 17:34:21.835475	2018-10-03 22:10:43.366324	276.0	
144485	test	2018-10-03 09:06:06.690094	thanos::sroute:cbef3b6a-79ea-4d5e-a215-b558a70...	FTL	trip-153855756668984584	IND282002AAD	NaN	IND474003AAA	Gwalior_HrihrNgr_I (Madhya Pradesh)	2018-10-03 17:34:21.835475	2018-10-03 22:10:43.366324	276.0	
144486	test	2018-10-03 09:06:06.690094	thanos::sroute:cbef3b6a-79ea-4d5e-a215-b558a70...	FTL	trip-153855756668984584	IND282002AAD	NaN	IND474003AAA	Gwalior_HrihrNgr_I (Madhya Pradesh)	2018-10-03 17:34:21.835475	2018-10-03 22:10:43.366324	276.0	
144487	test	2018-10-03 09:06:06.690094	thanos::sroute:cbef3b6a-79ea-4d5e-a215-b558a70...	FTL	trip-153855756668984584	IND282002AAD	NaN	IND474003AAA	Gwalior_HrihrNgr_I (Madhya Pradesh)	2018-10-03 17:34:21.835475	2018-10-03 22:10:43.366324	276.0	
144488	test	2018-10-03 09:06:06.690094	thanos::sroute:cbef3b6a-79ea-4d5e-a215-b558a70...	FTL	trip-153855756668984584	IND282002AAD	NaN	IND474003AAA	Gwalior_HrihrNgr_I (Madhya Pradesh)	2018-10-03 17:34:21.835475	2018-10-03 22:10:43.366324	276.0	

293 rows × 19 columns

In [33]:
```
dd[dd.destination_name.isna()]
```

Out[33]:

	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	actua
110	training	2018-09-25 08:53:04.377810	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	trip-153786558437756691	IND342601AAA	Piparcity_BsstdDPP_D (Rajasthan)	IND342902A1B	NaN	2018-09-26 05:04:49.254901	2018-09-26 06:58:08.054001	113.0	
111	training	2018-09-25 08:53:04.377810	thanos::sroute:4460a38d-ab9b-484e-bd4e-f4201d0...	FTL	trip-153786558437756691	IND342601AAA	Piparcity_BsstdDPP_D (Rajasthan)	IND342902A1B	NaN	2018-09-26 05:04:49.254901	2018-09-26 06:58:08.054001	113.0	
982	test	2018-10-01 20:56:18.155260	thanos::sroute:d0ebdacd-e09b-47d3-be77-c9c4a05...	FTL	trip-153842737815495661	IND573103AAA	Arsikere_HsnRdDPP_D (Karnataka)	IND577116AAA	NaN	2018-10-02 01:22:21.450243	2018-10-02 02:07:27.840862	45.0	
983	test	2018-10-01 20:56:18.155260	thanos::sroute:d0ebdacd-e09b-47d3-be77-c9c4a05...	FTL	trip-153842737815495661	IND573103AAA	Arsikere_HsnRdDPP_D (Karnataka)	IND577116AAA	NaN	2018-10-02 01:22:21.450243	2018-10-02 02:07:27.840862	45.0	
4882	training	2018-09-24 07:18:06.087341	thanos::sroute:2f43f11e-d3ba-4590-9355-82928e1...	FTL	trip-153777348608709328	IND202001AAB	Aligarh_KhirByps_I (Uttar Pradesh)	IND282002AAD	NaN	2018-09-24 15:02:13.760270	2018-09-24 18:49:23.454535	227.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
144478	test	2018-10-03 09:06:06.690094	thanos::sroute:cbef3b6a-79ea-4d5e-a215-b558a70...	FTL	trip-153855756668984584	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)	IND282002AAD	NaN	2018-10-03 09:06:06.690094	2018-10-03 17:34:21.835475	508.0	
144479	test	2018-10-03 09:06:06.690094	thanos::sroute:cbef3b6a-79ea-4d5e-a215-b558a70...	FTL	trip-153855756668984584	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)	IND282002AAD	NaN	2018-10-03 09:06:06.690094	2018-10-03 17:34:21.835475	508.0	
144480	test	2018-10-03 09:06:06.690094	thanos::sroute:cbef3b6a-79ea-4d5e-a215-b558a70...	FTL	trip-153855756668984584	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)	IND282002AAD	NaN	2018-10-03 09:06:06.690094	2018-10-03 17:34:21.835475	508.0	
144481	test	2018-10-03 09:06:06.690094	thanos::sroute:cbef3b6a-79ea-4d5e-a215-b558a70...	FTL	trip-153855756668984584	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)	IND282002AAD	NaN	2018-10-03 09:06:06.690094	2018-10-03 17:34:21.835475	508.0	
144482	test	2018-10-03 09:06:06.690094	thanos::sroute:cbef3b6a-79ea-4d5e-a215-b558a70...	FTL	trip-153855756668984584	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)	IND282002AAD	NaN	2018-10-03 09:06:06.690094	2018-10-03 17:34:21.835475	508.0	

261 rows × 19 columns

In [34]:
```
ddd = dd.copy()
```

In [35]:
```
missing_source_name = ddd.loc[ddd['source_name'].isnull(), 'source_center'].unique()
missing_source_name
```

Out[35]:
```
array(['IND342902A1B', 'IND577116AAA', 'IND282002AAD', 'IND465333A1B',
       'IND841301AAC', 'IND509103AAC', 'IND126116AAA', 'IND331022A1B',
       'IND505326AAB', 'IND852118A1B'], dtype=object)
```

In [36]:
```
missing_destination_name = ddd.loc[ddd['destination_name'].isnull(), 'destination_center'].unique()
missing_destination_name
```

Out[36]:
```
array(['IND342902A1B', 'IND577116AAA', 'IND282002AAD', 'IND465333A1B',
       'IND841301AAC', 'IND505326AAB', 'IND852118A1B', 'IND126116AAA',
       'IND509103AAC', 'IND221005A1A', 'IND250002AAC', 'IND331001A1C',
       'IND122015AAC'], dtype=object)
```

In [37]:
```
# 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()
```

Out[37]:
```
False
```

In [38]:
```
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
```

In [39]:
```
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
```

In [40]:
```
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
```

In [41]:
```
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
```

In [45]:
```
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])
```

In [46]:
```
ddd.source_name.value_counts()
```

Out[46]:
```
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
```

In [47]:
```
ddd.destination_name.value_counts()
```

Out[47]:
```
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..

In [49]:
```
261+290
```

Out[49]:
```
551
```

In [50]:
```
len(delhivery_data)
```

Out[50]:
```
144867
```

In [51]:
```
144867 - 551
```

Out[51]:
```
144316
```

In [52]:
```
df = dd.dropna()
```

In [53]:
```
df.isna().sum().any()
```

Out[53]:
```
False
```

In [54]:
```
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

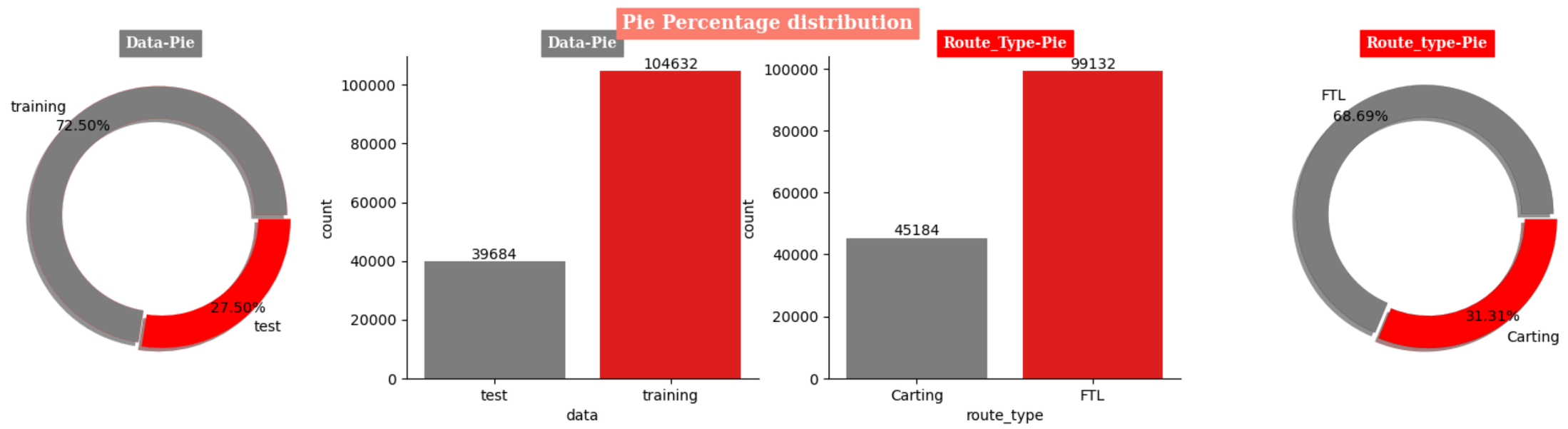
In [55]:
```
cp = ['gray','red','dimgrey','tomato','dimgray','orangered','k','salmon','gray','red','dimgrey','tomato','dimgray','orangered','k','salmon']
```

In [255…
```
df.sample()
```

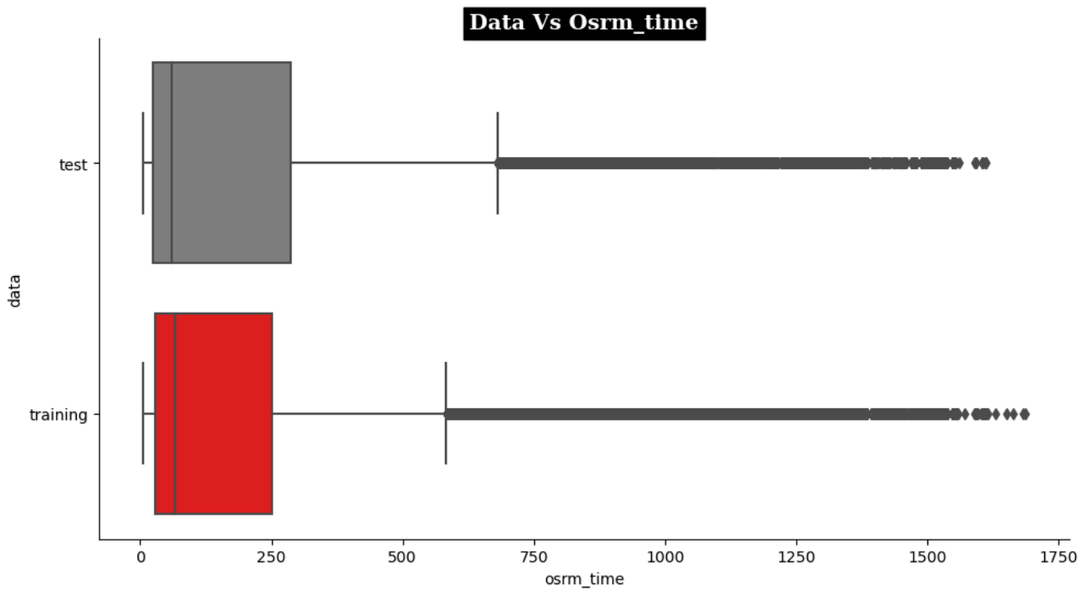
Out[255]:

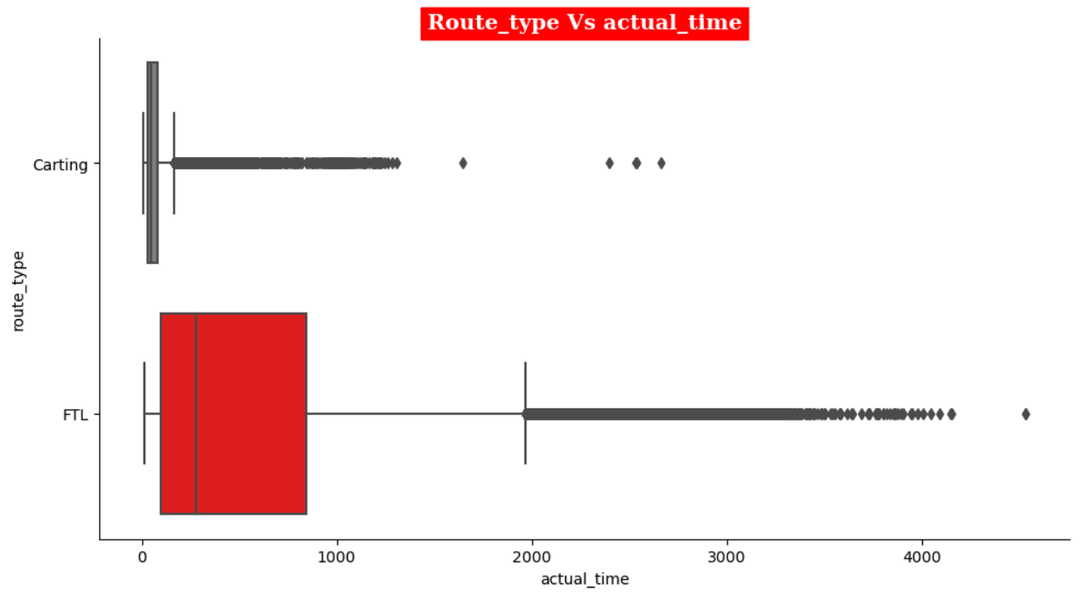
	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	destination_name	od_start_time	od_end_time	start_scan_to_end_scan	actua
92389	training	2018-09-14 23:36:50.771430	thanos::sroute:3f001d56-e933-4ba1-a7cf-26828f7...	Carting	trip-153696821077115152	IND515201AAA	Hindupur_Parigi_D (Andhra Pradesh)	IND515301AAA	Madakasira_RTCStand_D (Andhra Pradesh)	2018-09-15 01:35:41.452946	2018-09-15 02:46:18.759915	70.0	

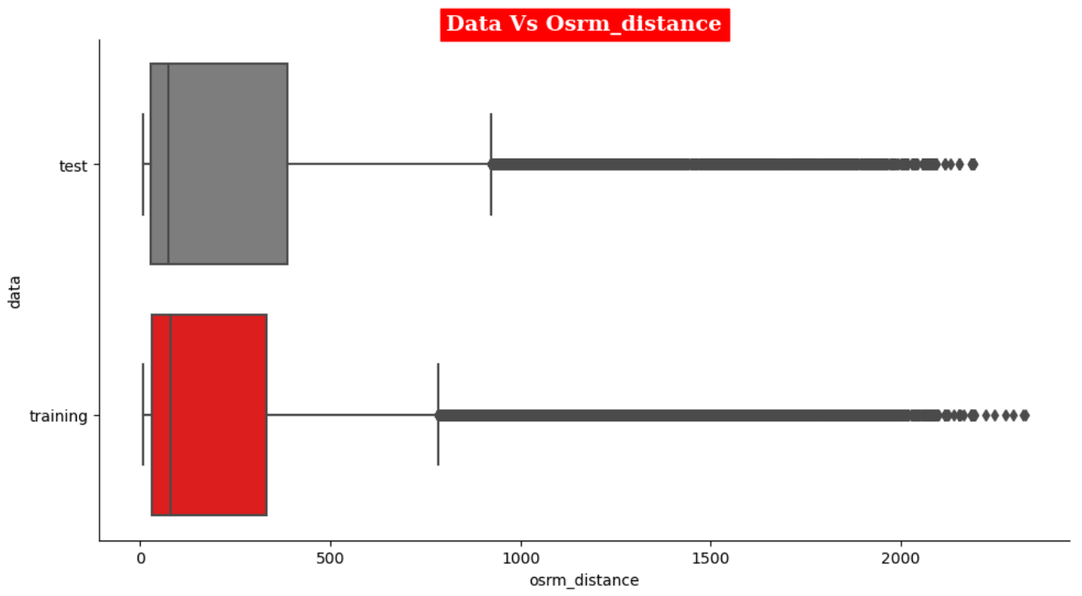
In [270…
```
plt.figure(figsize=(20,4))
plt.suptitle('Pie Percentage distribution',fontsize=13,fontfamily='serif',fontweight='bold',backgroundcolor=cp[-1],color='w')

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()
```

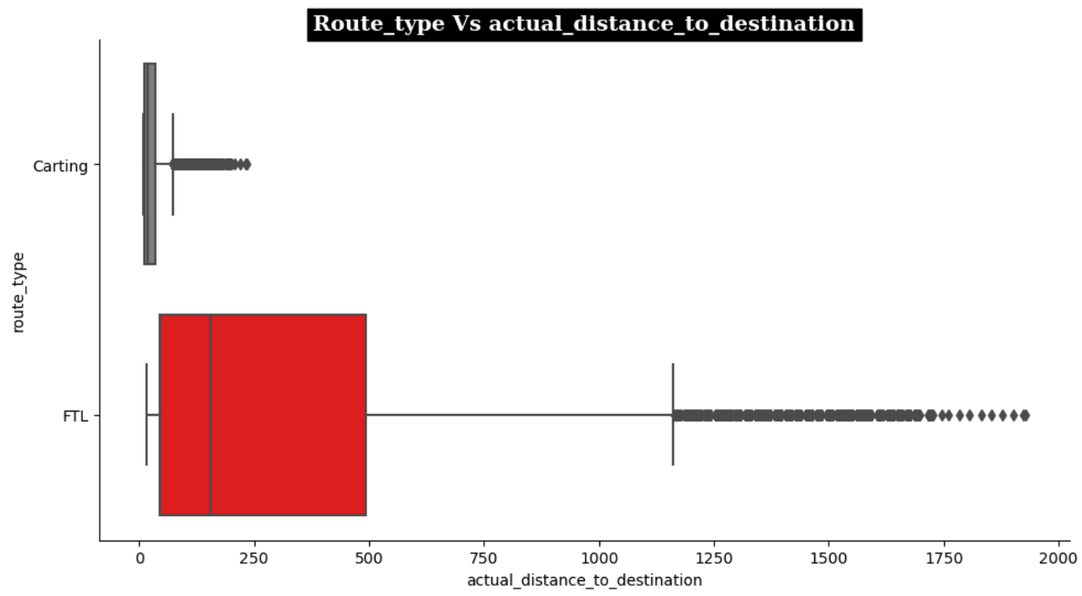


In [57]:
```
plt.figure(figsize=(25,13))
plt.style.use('default')
plt.style.use('seaborn-bright')

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.

In [58]:
```
# 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']]
```

Out[58]:

	segment_key	segment_actual_time	segment_actual_time_sum	segment_osrm_distance	segment_osrm_distance_sum	segment_osrm_time	segment_osrm_time_sum
0	trip-153741093647649320+IND388121AAA+IND388620AAB	14.0	14.0	11.965300	11.965300	11.0	11.0
1	trip-153741093647649320+IND388121AAA+IND388620AAB	10.0	24.0	9.759000	21.724300	9.0	20.0
2	trip-153741093647649320+IND388121AAA+IND388620AAB	16.0	40.0	10.815200	32.539497	7.0	27.0
3	trip-153741093647649320+IND388121AAA+IND388620AAB	21.0	61.0	13.022400	45.561897	12.0	39.0
4	trip-153741093647649320+IND388121AAA+IND388620AAB	6.0	67.0	3.915300	49.477200	5.0	44.0
...	...	...	...	...	...	...	...
144862	trip-153746066843555182+IND131028AAB+IND000000ACB	12.0	92.0	8.185800	65.348701	12.0	94.0
144863	trip-153746066843555182+IND131028AAB+IND000000ACB	26.0	118.0	17.372499	82.721199	21.0	115.0
144864	trip-153746066843555182+IND131028AAB+IND000000ACB	20.0	138.0	20.705299	103.426498	34.0	149.0
144865	trip-153746066843555182+IND131028AAB+IND000000ACB	17.0	155.0	18.888500	122.315002	27.0	176.0
144866	trip-153746066843555182+IND131028AAB+IND000000ACB	268.0	423.0	8.808800	131.123795	9.0	185.0

144316 rows × 7 columns

In [59]:
```
# 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
```

Out[59]:

	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	actua
0	trip-153671041653548748+IND209304AAA+IND000000ACB	trip-153671041653548748	training	FTL	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	2018-09-12 16:39:46.858469	2018-09-13 13:40:23.123744	1260.0	
1	trip-153671041653548748+IND462022AAA+IND209304AAA	trip-153671041653548748	training	FTL	2018-09-12 00:00:16.535741	Bhopal_Trnsport_H (Madhya Pradesh)	Kanpur_Central_H_6 (Uttar Pradesh)	2018-09-12 00:00:16.535741	2018-09-12 16:39:46.858469	999.0	
2	trip-153671042288605164+IND561203AAB+IND562101AAA	trip-153671042288605164	training	Carting	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	2018-09-12 02:03:09.655591	2018-09-12 03:01:59.598855	58.0	
3	trip-153671042288605164+IND572101AAA+IND561203AAB	trip-153671042288605164	training	Carting	2018-09-12 00:00:22.886430	Tumkur_Veersagr_I (Karnataka)	Doddablpur_ChikaDPP_D (Karnataka)	2018-09-12 00:00:22.886430	2018-09-12 02:03:09.655591	122.0	
4	trip-153671043369099517+IND000000ACB+IND160002AAC	trip-153671043369099517	training	FTL	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)	Chandigarh_Mehmdpur_H (Punjab)	2018-09-14 03:40:17.106733	2018-09-14 17:34:55.442454	834.0	
...	...	...	...	...	...	...	...	...	...	...	
26217	trip-153861115439069069+IND628204AAA+IND627657AAA	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	Tirchchndr_Shnmgprm_D (Tamil Nadu)	Thisayanvilai_UdnkdiRD_D (Tamil Nadu)	2018-10-04 02:29:04.272194	2018-10-04 03:31:11.183797	62.0	
26218	trip-153861115439069069+IND628613AAA+IND627005AAA	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	Peikulam_SriVnktpm_D (Tamil Nadu)	Tirunelveli_VdkkuSrt_I (Tamil Nadu)	2018-10-04 04:16:39.894872	2018-10-04 05:47:45.162682	91.0	
26219	trip-153861115439069069+IND628801AAA+IND628204AAA	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	Eral_Busstand_D (Tamil Nadu)	Tirchchndr_Shnmgprm_D (Tamil Nadu)	2018-10-04 01:44:53.808000	2018-10-04 02:29:04.272194	44.0	
26220	trip-153861118270144424+IND583119AAA+IND583101AAA	trip-153861118270144424	test	FTL	2018-10-03 23:59:42.701692	Sandur_WrdN1DPP_D (Karnataka)	Bellary_Dc (Karnataka)	2018-10-04 03:58:40.726547	2018-10-04 08:46:09.166940	287.0	
26221	trip-153861118270144424+IND583201AAA+IND583119AAA	trip-153861118270144424	test	FTL	2018-10-03 23:59:42.701692	Hospet (Karnataka)	Sandur_WrdN1DPP_D (Karnataka)	2018-10-04 02:51:44.712656	2018-10-04 03:58:40.726547	66.0	

26222 rows × 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

In [60]:
```
# 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
```

Out[60]:

	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	actua
0	trip-153671041653548748+IND209304AAA+IND000000ACB	trip-153671041653548748	training	FTL	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	2018-09-12 16:39:46.858469	2018-09-13 13:40:23.123744	1260.0	
1	trip-153671041653548748+IND462022AAA+IND209304AAA	trip-153671041653548748	training	FTL	2018-09-12 00:00:16.535741	Bhopal_Trnsport_H (Madhya Pradesh)	Kanpur_Central_H_6 (Uttar Pradesh)	2018-09-12 00:00:16.535741	2018-09-12 16:39:46.858469	999.0	
2	trip-153671042288605164+IND561203AAB+IND562101AAA	trip-153671042288605164	training	Carting	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	2018-09-12 02:03:09.655591	2018-09-12 03:01:59.598855	58.0	
3	trip-153671042288605164+IND572101AAA+IND561203AAB	trip-153671042288605164	training	Carting	2018-09-12 00:00:22.886430	Tumkur_Veersagr_I (Karnataka)	Doddablpur_ChikaDPP_D (Karnataka)	2018-09-12 00:00:22.886430	2018-09-12 02:03:09.655591	122.0	
4	trip-153671043369099517+IND000000ACB+IND160002AAC	trip-153671043369099517	training	FTL	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)	Chandigarh_Mehmdpur_H (Punjab)	2018-09-14 03:40:17.106733	2018-09-14 17:34:55.442454	834.0	
...	...	...	...	...	...	...	...	...	...	...	
26217	trip-153861115439069069+IND628204AAA+IND627657AAA	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	Tirchchndr_Shnmgprm_D (Tamil Nadu)	Thisayanvilai_UdnkdiRD_D (Tamil Nadu)	2018-10-04 02:29:04.272194	2018-10-04 03:31:11.183797	62.0	
26218	trip-153861115439069069+IND628613AAA+IND627005AAA	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	Peikulam_SriVnktpm_D (Tamil Nadu)	Tirunelveli_VdkkuSrt_I (Tamil Nadu)	2018-10-04 04:16:39.894872	2018-10-04 05:47:45.162682	91.0	
26219	trip-153861115439069069+IND628801AAA+IND628204AAA	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	Eral_Busstand_D (Tamil Nadu)	Tirchchndr_Shnmgprm_D (Tamil Nadu)	2018-10-04 01:44:53.808000	2018-10-04 02:29:04.272194	44.0	
26220	trip-153861118270144424+IND583119AAA+IND583101AAA	trip-153861118270144424	test	FTL	2018-10-03 23:59:42.701692	Sandur_WrdN1DPP_D (Karnataka)	Bellary_Dc (Karnataka)	2018-10-04 03:58:40.726547	2018-10-04 08:46:09.166940	287.0	
26221	trip-153861118270144424+IND583201AAA+IND583119AAA	trip-153861118270144424	test	FTL	2018-10-03 23:59:42.701692	Hospet (Karnataka)	Sandur_WrdN1DPP_D (Karnataka)	2018-10-04 02:51:44.712656	2018-10-04 03:58:40.726547	66.0	

26222 rows × 22 columns

In [61]:
```
segment_agg_data.sample()
```

Out[61]:

	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_
4965	trip-153704666810685062+IND173025AAA+IND160002AAC	trip-153704666810685062	training	FTL	2018-09-15 21:24:28.108007	PaontSahib_Gurudwar_D (Himachal Pradesh)	Chandigarh_Mehmdpur_H (Punjab)	2018-09-16 09:10:26.756767	2018-09-16 14:11:04.351703	300.0	

In [63]:
```
# de = segment_agg_data.drop(columns=['source_city','source_state','source_place','destination_place','destination_city','destination_state'])
de = segment_agg_data.copy()
```

In [64]:
```
de.sample()
```

Out[64]:

	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_
4962	trip-153704666399260818+IND421302AAG+IND401104AAA	trip-153704666399260818	training	Carting	2018-09-15 21:24:23.992906	Bhiwandi_Mankoli_HB (Maharashtra)	Mumbai_MiraRd_IP (Maharashtra)	2018-09-15 21:24:23.992906	2018-09-16 01:16:04.776133	231.0	

In [ ]:
```
# # 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]
```

In [65]:
```
# 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
```

In [66]:
```
de[['source_city', 'source_place', 'source_state']] = de['source_name'].apply(lambda x: pd.Series(extract_info(x)))
```

In [67]:
```
de[['destination_city', 'destination_place', 'destination_state']] = de['destination_name'].apply(lambda x: pd.Series(extract_info(x)))
```

In [68]:
```
de
```

Out[68]:

	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	actua
0	trip-153671041653548748+IND209304AAA+IND000000ACB	trip-153671041653548748	training	FTL	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	2018-09-12 16:39:46.858469	2018-09-13 13:40:23.123744	1260.0	
1	trip-153671041653548748+IND462022AAA+IND209304AAA	trip-153671041653548748	training	FTL	2018-09-12 00:00:16.535741	Bhopal_Trnsport_H (Madhya Pradesh)	Kanpur_Central_H_6 (Uttar Pradesh)	2018-09-12 00:00:16.535741	2018-09-12 16:39:46.858469	999.0	
2	trip-153671042288605164+IND561203AAB+IND562101AAA	trip-153671042288605164	training	Carting	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	2018-09-12 02:03:09.655591	2018-09-12 03:01:59.598855	58.0	
3	trip-153671042288605164+IND572101AAA+IND561203AAB	trip-153671042288605164	training	Carting	2018-09-12 00:00:22.886430	Tumkur_Veersagr_I (Karnataka)	Doddablpur_ChikaDPP_D (Karnataka)	2018-09-12 00:00:22.886430	2018-09-12 02:03:09.655591	122.0	
4	trip-153671043369099517+IND000000ACB+IND160002AAC	trip-153671043369099517	training	FTL	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)	Chandigarh_Mehmdpur_H (Punjab)	2018-09-14 03:40:17.106733	2018-09-14 17:34:55.442454	834.0	
...	...	...	...	...	...	...	...	...	...	...	
26217	trip-153861115439069069+IND628204AAA+IND627657AAA	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	Tirchchndr_Shnmgprm_D (Tamil Nadu)	Thisayanvilai_UdnkdiRD_D (Tamil Nadu)	2018-10-04 02:29:04.272194	2018-10-04 03:31:11.183797	62.0	
26218	trip-153861115439069069+IND628613AAA+IND627005AAA	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	Peikulam_SriVnktpm_D (Tamil Nadu)	Tirunelveli_VdkkuSrt_I (Tamil Nadu)	2018-10-04 04:16:39.894872	2018-10-04 05:47:45.162682	91.0	
26219	trip-153861115439069069+IND628801AAA+IND628204AAA	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	Eral_Busstand_D (Tamil Nadu)	Tirchchndr_Shnmgprm_D (Tamil Nadu)	2018-10-04 01:44:53.808000	2018-10-04 02:29:04.272194	44.0	
26220	trip-153861118270144424+IND583119AAA+IND583101AAA	trip-153861118270144424	test	FTL	2018-10-03 23:59:42.701692	Sandur_WrdN1DPP_D (Karnataka)	Bellary_Dc (Karnataka)	2018-10-04 03:58:40.726547	2018-10-04 08:46:09.166940	287.0	
26221	trip-153861118270144424+IND583201AAA+IND583119AAA	trip-153861118270144424	test	FTL	2018-10-03 23:59:42.701692	Hospet (Karnataka)	Sandur_WrdN1DPP_D (Karnataka)	2018-10-04 02:51:44.712656	2018-10-04 03:58:40.726547	66.0	

26222 rows × 28 columns

In [69]:
```
de[(de['source_place']=='') | (de['destination_place']=='')]
```

Out[69]:

	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_distan
7	trip-153671052974046625+IND583101AAA+IND583201AAA	trip-153671052974046625	training	FTL	2018-09-12 00:02:09.740725	Bellary_Dc (Karnataka)	Hospet (Karnataka)	2018-09-12 00:02:09.740725	2018-09-12 02:34:10.515593	152.0	
9	trip-153671052974046625+IND583201AAA+IND583119AAA	trip-153671052974046625	training	FTL	2018-09-12 00:02:09.740725	Hospet (Karnataka)	Sandur_WrdN1DPP_D (Karnataka)	2018-09-12 02:34:10.515593	2018-09-12 03:54:43.114421	80.0	
19	trip-153671110078355292+IND121004AAB+IND121001AAA	trip-153671110078355292	training	Carting	2018-09-12 00:11:40.783923	FBD_Balabhgarh_DPC (Haryana)	Faridabad (Haryana)	2018-09-12 00:11:40.783923	2018-09-12 00:50:10.814399	38.0	
33	trip-153671173668736946+IND110043AAA+IND110078AAA	trip-153671173668736946	training	Carting	2018-09-12 00:22:16.687619	Delhi_Nangli_IP (Delhi)	Janakpuri (Delhi)	2018-09-12 00:22:16.687619	2018-09-12 01:29:19.277412	67.0	
80	trip-153671320807895983+IND121004AAB+IND121102AAA	trip-153671320807895983	training	Carting	2018-09-12 00:46:48.079257	FBD_Balabhgarh_DPC (Haryana)	Palwal (Haryana)	2018-09-12 00:46:48.079257	2018-09-12 01:53:32.471405	66.0	
...	...	...	...	...	...	...	...	...	...	...	
26118	trip-153860849934816308+IND110078AAA+IND110043AAA	trip-153860849934816308	test	Carting	2018-10-03 23:14:59.348414	Janakpuri (Delhi)	Delhi_Nangli_IP (Delhi)	2018-10-04 01:32:14.530264	2018-10-04 03:05:32.479193	93.0	
26153	trip-153860958923357924+IND842003AAB+IND482002AAA	trip-153860958923357924	test	Carting	2018-10-03 23:33:09.233829	Jabalpur_Adhartal_IP (Madhya Pradesh)	Jabalpur (Madhya Pradesh)	2018-10-03 23:33:09.233829	2018-10-04 07:48:23.711056	495.0	
26180	trip-153861007249500192+IND842001AAA+IND846004AAA	trip-153861007249500192	test	FTL	2018-10-03 23:41:12.495257	Muzaffrpur_Bbganj_I (Bihar)	Darbhanga (Bihar)	2018-10-03 23:41:12.495257	2018-10-04 02:17:56.235080	156.0	
26181	trip-153861007249500192+IND846004AAA+IND847103AAA	trip-153861007249500192	test	FTL	2018-10-03 23:41:12.495257	Darbhanga (Bihar)	Benipur_Javahar_D (Bihar)	2018-10-04 02:17:56.235080	2018-10-04 04:20:42.531207	122.0	
26221	trip-153861118270144424+IND583201AAA+IND583119AAA	trip-153861118270144424	test	FTL	2018-10-03 23:59:42.701692	Hospet (Karnataka)	Sandur_WrdN1DPP_D (Karnataka)	2018-10-04 02:51:44.712656	2018-10-04 03:58:40.726547	66.0	

782 rows × 28 columns

In [70]:
```
de.loc[de['source_place']=='','source_place']=de['source_city']
de.loc[de['destination_place']=='','destination_place']=de['destination_city']
```

In [71]:
```
de[de.source_place.isna()]
```

Out[71]:

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_act

In [72]:
```
de.isna().sum()
```

Out[72]:
```
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
```

In [73]:
```
#de = de.drop(columns=['source_city','source_state','source_place','destination_city', 'destination_place', 'destination_state'])
```

In [74]:
```
de.loc[de.source_city=='Bangalore','source_city']='Bengaluru'
de.loc[de.destination_city=='Bangalore','destination_city']='Bengaluru'
```

In [75]:
```
np.set_printoptions(threshold=np.inf)
```

In [76]:
```
de['source_city'].unique()
```

Out[76]:
```
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', 'Kollegala', 'Mysore', 'Hunsur',
       'HDKote', 'Gonikoppal', 'Patan', 'Bhabhar', 'Vizag', 'Rajamundry',
       'Goa', 'Sawantwadi', 'Kankavali', 'Sonipat', 'Moradabad',
       'Rudrapur', 'Himmatnagar', 'Khedbrahma', 'Modasa', 'Jamshedpur',
       'Pondicherry', 'Cuddalore', 'Chidambaram', 'Sirkazhi', 'Karaikal',
       'Thiruvarur', 'Nagapttinm', 'MAA', 'Anand', 'Khambhat', 'Udgir',
       'Latur', 'Degloor', 'Nadiad', 'Umreth', 'Villupuram', 'Virudhchlm',
       'Pennadam', 'Chinnasalem', 'Panruti', 'Neyveli', 'Purulia', 'Hura',
       'Rghunthpur', 'Jhalda', 'Bhubaneshwar', 'Bamangola', 'Meham',
       'Tiruppattur', 'Ambur', 'Kotdwara', 'Haridwar', 'Medak',
       'Narsapur', 'Kamareddy', 'Yellareddy', 'Bodhan', 'Banswada',
       'Dhrangadhra', 'Halvad', 'Gandhidham', 'Gangavathi', 'Koppal',
       'Ghumarwin', 'JognderNgr', 'Jahu', 'ChandroknaRD', 'Kharagpur',
       'AmaDubi', 'Agra', 'Sitapur', 'Biswan', 'Lakhimpur', 'Gola',
       'Canacona', 'Bilimora', 'SultnBthry', 'Lucknow', 'Vellore', 'Bhuj',
       'Anjar', 'Dinhata', 'BOM', 'Margherita', 'Boisar', 'Dahanu',
       'Chodavaram', 'Tezpur', 'Bomdila', 'Koduru', 'Rajampet',
       'Tirupati', 'Puttur', 'Sriklahsti', 'Gudur', 'Venktagiri', 'Pen',
       'Roha', 'Mahad', 'AMD', 'Ahmedabad', 'Faizabad', 'Gosainganj',
       'Gandhinagar', 'Muzaffrpur', 'Phagwara', 'Betul', 'Itarsi',
       'Pandhurna', 'Panskura', 'Haldia', 'Tamluk', 'Karur', 'BLR',
       'Rasipurm', 'Sankari', 'Jorhat', 'Bokakhat', 'PNQ', 'Aligarh',
       'Mainpuri', 'Shikohabad', 'Firozabad', 'Srikakulam', 'Rajam',
       'Palakonda', 'Parvathipuram', 'Bobbili', 'Tekkali', 'Palasa',
       'Narasnpeta', 'Paralakhemundi', 'Dehradun', 'Hajo', 'NOI',
       'Jassur', 'Dalhousie', 'Chamba', 'Baharampur', 'Dhulian',
       'Hoskote', 'Shajapur', 'Shujalpur', 'Pachore', 'OK', 'Ludhiana',
       'GreaterThane', 'Janakpuri', 'Amritsar', 'Tirupur', 'Attur',
       'Salem', 'Tirchngode', 'Darjeeling', 'Mirik', 'Tiruchi', 'Noida',
       'Rangia', 'Dhubri', 'Bilasipara', 'Kokrajhar', 'Tura', 'Ajmer',
       'Pali', 'Jodhpur', 'Amroha', 'Gajraula', 'Rampur', 'Jhansi',
       'Dholpur', 'Gwalior', 'Thirthurpondi', 'Pushpavanam', 'Ranchi',
       'Guna', 'Ashokngr', 'Raver', 'Hassan', 'Jairampur', 'Chamoli',
       'Karnaprayag', 'Gohpur', 'Dhemaji', 'Silapathar', 'Gopiganj',
       'Varanasi', 'Dharmapuri', 'Hubli', 'Bailhongal', 'Gokak', 'Gadag',
       'Rona', 'Bagalkot', 'Ramdurg', 'Duddhi', 'Renukoot', 'Anpara',
       'Singrauli', 'Panipat', 'Sasaram', 'Tangi', 'Davangere',
       'Ranebennur', 'Vrindavan', 'Chittaurgarh', 'Rajsamand', 'Solapur',
       'Pratapgarh', 'Del', 'Moga', 'Muktsar', 'Jagatsghpr', 'Paradip',
       'Mangalore', 'Barshi', 'Osmanabad', 'Vinukonda', 'Ongole',
       'Kanigiri', 'Kavali', 'Achrol', 'LowerParel', 'Sagara', 'Sirsi',
       'Deoband', 'Muzaffrngr', 'Tikamgarh', 'Satna', 'Ghaziabad',
       'Chhapra', 'BiharSarif', 'Rajgir', 'Jehanabad', 'Nawada',
       'Pallakad', 'Vadakkencherry', 'Thrissur', 'Aluva', 'Kanakapura',
       'Ramanagara', 'Mandya', 'Srirangapatna', 'Roorkee', 'Rishikesh',
       'Aurangabad', 'Surathkal', 'Vadodara', 'Barh', 'Sheikhpura',
       'Godhra', 'Coimbatore', 'Bhadrak', 'Karanjia', 'Kendujhar', 'Joda',
       'Narnaul', 'Rewari', 'Bhiwadi', 'Hisar', 'Ganga', 'Hanumangarh',
       'Bihta', 'Arrah', 'Jhajjar', 'Silchar', 'Kabuganj', 'Bardhaman',
       'Asansol', 'Rupnarayanpur', 'Midnapore', 'Sillod', 'Jalna',
       'Nellore', 'Katwa', 'Chapra', 'Nakashipara', 'Plassey',
       'Thamarassery', 'Safidon', 'Kaithal', 'Kurukshetra', 'Pehowa',
       'Udaipur', 'Kaikaluru', 'Eluru', 'Machilipatnam', 'Gudivada',
       'Nazirpur', 'Nowda', 'Domkal', 'Devarakonda', 'Haliya',
       'Kalwakurthy', 'Kadthal', 'Vikarabad', 'Rampurhat', 'Morgram',
       'Kandi', 'Khargram', 'Ghanashyampur', 'Visakhapatnam', 'Lalgola',
       'Murshidabad', 'Jangipur', 'Ragunthgnj', 'Sagardighi',
       'AhmedNagar', 'Ashti', 'Parner', 'Bilaspur', 'Pilibhit',
       'Hailakandi', 'Badarpur', 'Teok', 'BilaspurHP', 'Mandi',
       'SundarNgr', 'Kakinada', 'Chitradurga', 'Hiriyur', 'Amalapuram',
       'Madhubani', 'Jaynagar', 'Kalka', 'Solan', 'Nalagarh', 'Buldhana',
       'Akola', 'Shegaon', 'Karad', 'Islampur', 'Chiplun', 'JoguGadwal',
       'Raichur', 'Modinagar', 'Meerut', 'Madhepura', 'Supaul',
       'Triveninganj', 'Saharsa', 'Purnia', 'Simrahi', 'Araria',
       'Narpatganj', 'Sitamari', 'Sheohar', 'Benipatti', 'Atmakur',
       'Bngnpalle', 'Nandyal', 'Dandeli', 'Mallapur', 'Chikodi', 'Athani',
       'Rohtak', 'Jind', 'Gohana', 'Patiala', 'Sunam', 'Nasirabad',
       'Asind', 'Darbhanga', 'Benipur', 'Jhanjharpur', 'Channaraya',
       'Naugchia', 'Katihar', 'Puttaprthi', 'Kadiri', 'Dharmavram',
       'Rayachoti', 'Pulivendula', 'Ambala', 'YamunaNagar', 'PaontSahib',
       'Kishangarh', 'Degana', 'Makrana', 'Merta', 'Parbatsar', 'Korba',
       'Pithorgarh', 'Nainital', 'Almora', 'Ranikhet', 'Deoghar', 'Alwar',
       'Bharatpur', 'Gorakhpur', 'Deoria', 'Kaptanganj', 'Padrauna',
       'Salempur', 'Dhaka', 'Bettiah', 'Narktiganj', 'Bhatpara',
       'Mungeli', 'Dumka', 'Jamtara', 'Pakur', 'Bangana', 'Sujanpur',
       'Nadaun', 'Bahadurgarh', 'Kanth', 'Thakurdwara', 'Bijnor',
       'Dhampur', 'Najibabad', 'Nichlaul', 'Warangal', 'Khanpur',
       'Rayaparthi', 'Aonla', 'Sambhal', 'Chandausi', 'Dhar', 'Bagnan',
       'Kolaghat', 'Ghatal', 'Naraingarh', 'Kashipur', 'Ramnagar',
       'Ratanpura', 'Bariya', 'Sikandarpur', 'Gondia', 'Motihari',
       'Zahirabad', 'Narayankhed', 'Humnabad', 'Bidar', 'Gooty',
       'Kalyandurg', 'Guntakal', 'Rayadurgam', 'Samana', 'Patran',
       'Bhadrachalam', 'Manuguru', 'Sathupally', 'Baraut', 'Bassi',
       'Dausa', 'Lalsot', 'Gangapur', 'Hindaun', 'Karauli', 'Sikar',
       'Nawalgarh', 'Jamnagar', 'Khambhalia', 'Bhatiya', 'Kakdwip',
       'Fatepur', 'Amravati', 'Kalluvathukal', 'Attingal',
       'Kazhakkoottam', 'Surendranagar', 'Limbdi', 'Chotila', 'Dudu',
       'Phulera', 'Renwal', 'Buxar', 'Dumraon', 'DalsinghSarai', 'Rusera',
       'Manjhaul', 'Khurja', 'Jewar', 'Anupshahar', 'Pahasu',
       'Trivandrum', 'Neyatinkra', 'Etawah', 'Auraiya', 'Jasai',
       'Bhagalpur', 'Banka', 'Panaji', 'Raikot', 'Jagraon', 'GZB',
       'Hapur', 'Pilkhuwa', 'Dholi', 'Machhiwara', 'Chhata', 'Luxettipet',
       'Vemulawada', 'Metpally', 'Jagtial', 'Mancherial', 'Karimnagar',
       'Kottayam', 'Tiruvalla', 'Parakkdavu', 'Khurdha', 'Rajpura',
       'SirhindFatehgarh', 'Khanna', 'Pthnmthitt', 'Kollam', 'Punalur',
       'Kottarakkara', 'Adoor', 'Dhule', 'Sakri', 'Shindkheda', 'Shahada',
       'Nandurbar', 'DehriSone', 'Brahmapuri', 'Gadchiroli', 'Ramagundam',
       'Gomoh', 'Chalisgaon', 'Wardha', 'Barnala', 'Hindupur',
       'Ghatampur', 'Upleta', 'Mangrol', 'Banda', 'Fatehpur', 'Akbarpur',
       'Pukhrayan', 'Orai', 'Bhanvad', 'Mejia', 'Basti', 'Dibrugarh',
       'Khonsa', 'Digboi', 'Mussoorie', 'Kalpetta', 'Phalodi', 'Barmer',
       'Pokhran', 'Gangarampr', 'Changlang', 'Sidhi', 'Churhat', 'Vansda',
       'Bishnupur', 'Guskhara', 'Panagarh', 'Bolpur', 'Nanoor',
       'Mainaguri', 'Mathabhang', 'Jammu', 'Kathua', 'Samba', 'Bhusawal',
       'Burhanpur', 'Narsinghgarh', 'Hyd', 'Nalbari', 'Sendhwa',
       'Sholinghur', 'Ranipet', 'Kalpakkam', 'Talegaon', 'Rajgurunagar',
       'Kittur', 'SrinagarUK', 'Berhampur', 'Bishwanath', 'LakhimpurN',
       'Likabali', 'Shillong', 'Shimoga', 'Saundatti', 'Chomu', 'Gonda',
       'Balrampur', 'Tulsipur', 'Manapparai', 'Melur', 'Kandukur',
       'Ghazipur', 'Paota', 'Kotputli', 'Masaurhi', 'Guruvayoor',
       'Chetpet', 'Polur', 'Arani', 'Wai', 'Satara', 'Khandala',
       'Bhiwani', 'Udupi', 'Kundapura', 'Ankola', 'Bhatkal', 'Honnavar',
       'Kumta', 'Karkala', 'Moodbidri', 'GGN', 'Patancheru', 'Alappuzha',
```

```
'Haripad', 'Kozhikode', 'Vadakara', 'Koyilandy', 'Kallachi',
'Kumbakonam', 'Mylduthuri', 'Mannargudi', 'Rameswram',
'Muthukulathur', 'Narikkudi', 'Shirur', 'Ooty', 'Mahabubnagar',
'Bijnapally', 'Jadcherla', 'Pattukotai', 'Aranthangi',
'Peravurani', 'Ponnamaravathi', 'Karaikudi', 'Karimganj',
'Srisailam', 'Lalpet', 'Thuraiyur', 'Musiri', 'Perambalur',
'Ariyalur', 'Jayamkondan', 'Karwar', 'Parwanoo', 'Forbesganj',
'Raniganj', 'Madurai', 'Rajpalayam', 'Sivakasi', 'Maharajapuram',
'Sankaran', 'Sathyamangalam', 'Gobicheti', 'Anthiyour', 'Cjb',
'Ratlam', 'Jaora', 'Nabha', 'Usilampatti', 'Kattappana', 'Khurai',
'Mungaoli', 'Nuzvid', 'Vuyyuru', 'Koppa', 'Krishnarajpet',
'Nagamangala', 'Ramanathapura', 'Madikeri', 'Khatauli', 'Tiptur',
'Arsikere', 'Draksharamam', 'Weir', 'Kherli', 'Kolar',
'Chintamani', 'Mulbagal', 'Bethamangala', 'Bangarapet', 'Pollachi',
'Udumalpet', 'Haveri', 'NeemKaThana', 'Baheri', 'Raxaul', 'Chakia',
'Dharapuram', 'Kangayam', 'Tirpur', 'Mohania', 'Naugarh',
'Arakkonam', 'Kanchipuram', 'Kallikkad', 'Malemruvathur',
'Mahbubabad', 'Yellandu', 'Tirunelveli', 'Vallior', 'Marthandam',
'Bhavnagar', 'Amreli', 'Thisayanvilai', 'Tirchchndr', 'Peikulam',
'Eral', 'Kusumnchi', 'Kodad', 'Godda', 'Dhanbad', 'Mahadevpur',
'Bhupalpally', 'Mulugu', 'Jammikunta', 'Narsingpur', 'Amd',
'Manthani', 'SikandraRao', 'Etah', 'Jalesar', 'Mahoba', 'Bhind',
'Valsad', 'Navsari', 'Bagepalli', 'Chikblapur', 'Chhaygaon',
'Manamelkudi', 'Oriyur', 'Thiruvadanai', 'Sivaganga', 'Kanti',
'Saraiya', 'Malegaon', 'Manmad', 'Sindhanur', 'Murbad', 'Asangaon',
'Bhuvanagiri', 'Kanker', 'Unjha', 'Jaleswar', 'Malda', 'Balipara',
'Pathankot', 'Bhubaneswar', 'Sehore', 'Ashta', 'Erode', 'Gotan',
'Jalgaon', 'Silvassa', 'Mau', 'Balasore', 'Udala', 'Nagaur',
'Tarnau', 'Bhilwara', 'Ghanpur', 'Jangaon', 'Hazaribag',
'JhumriTlya', 'Dharwad', 'Chhatarpur', 'Panna', 'Dahod',
'Bareilly', 'Faridpur', 'Mandapeta', 'Tuni', 'Jeypore', 'Koraput',
'Wanaparthy', 'Ramnthpurm', 'Paramakudi', 'Kekri', 'Bijainagar',
'Beawar', 'Bilara', 'Sankaramangalam', 'Shoranur', 'Arimbur',
'Pazhayannur', 'Chikhli', 'Mehkar', 'Khamgaon', 'Ratia', 'Cumbum',
'Theni', 'Sakleshpur', 'Mudigere', 'Kotagiri', 'HazratJandaha',
'Samastipur', 'Nawanshahr', 'Bina', 'Ukkadagatri', 'Malur',
'Lonavala', 'Avinashi', 'Jhunjhunu', 'Khetri', 'AurngbadBR',
'Ambah', 'Chandpur', 'Madhupur', 'Sahebganj', 'Shirpur', 'Dadri',
'Husnabad', 'Kaman', 'Bewar', 'Manvi', 'Raipur', 'Bellmpalli',
'Kaghaznagar', 'Chinnur', 'Harraiya', 'Bareli', 'Nanjangud',
'Mothkur', 'Chhindwara', 'Lakhnadon', 'Hansi', 'Salur', 'Phulpur',
'Soraon', 'Mananthavady', 'Maihar', 'Rewa', 'Srivijaynagar',
'Suratgarh', 'Thoppur', 'Bongaigaon', 'Barpeta', 'Chopan',
'Addanki', 'Chimkurthy', 'Markapur', 'Bikaner', 'Didwana',
'Challakere', 'Molakalmuru', 'ChrkhiDdri', 'Blr', 'Sirsa',
'Nandigama', 'Dhone', 'Bhadra', 'Tirurangadi', 'Malappuram',
'Baddi', 'Mariani', 'Pupri', 'Sonepur', 'Karnal', 'Malerkotla',
'Giridih', 'Sahatwar', 'Sagar', 'Kushinagar', 'Pangodu', 'Shamli',
'Katni', 'Barhi', 'Rath', 'Konch', 'Hamirpur', 'Umaria', 'Koratla',
'Sitarganj', 'Anakapalle', 'Narsiptnm', 'Akhnoor', 'MirzapurWB',
'Golaghat', 'Sivasagar', 'Pasighat', 'Marakkanam', 'Dohrighat',
'Ghosi', 'Dhekiajuli', 'Mangaldoi', 'Reengus', 'Nokha', 'Bokaro',
'Peterbar', 'Ramgarh', 'Tandur', 'Shadnagar', 'Badnaur', 'Seoni',
'Mandla', 'Dharamshala', 'DehraGopipur', 'Amb', 'Kilimanoor',
'Nabarangpr', 'PaliBirsighpr', 'Pilani', 'Jagdishpur', 'Dwarka',
'Ambasamdrm', 'Tenkasi', 'Kolasib', 'Haldwani', 'Bheemunipatnam',
'Vizianagaram', 'Kanhangad', 'Manjeshwar', 'Anandnagar',
'Maharajganj', 'RaisingNgr', 'Anupgarh', 'Balotra', 'Jaisalmer',
'Vidisha', 'GanjBasoda', 'Malvan', 'Tezu', 'Piparcity', 'Lakhipur',
'Jaunpur', 'Banswara', 'Sujangarh', 'Kunnathund', 'Belgaum',
'Khanapur', 'Chalakudy', 'Irinjlkuda', 'Angamaly', 'Jath',
'Bijapur', 'Coonoor', 'Chikmagalur', 'Palampur', 'Fatehabad',
'Barwala', 'Bhadaur', 'Tinusukia', 'Chabua', 'DoomDooma', 'Namsai',
'Dalkhola', 'Dharmanagr', 'Airport', 'MughalSarai', 'Manthuka',
'Kayamkulam', 'Aizawl', 'Champhai', 'Tirur', 'Cochin', 'Uchila',
'Shevgaon', 'Paithan', 'Beed', 'Georai', 'Nandikotkr',
'Betamcherla', 'Nilambur', 'HanumanJNC', 'Bikramgang', 'Dinara',
'Itahar', 'Kaliyaganj', 'Manikchak', 'Sihora', 'Rajkot',
'Bulndshahr', 'Chaksu', 'Majalgaon', 'Mandsaur', 'Sitamau',
'Kirauli', 'Roing', 'Krishnagiri', 'Pachora', 'Erandol', 'Amalner',
'Pataudi', 'Naharlagun', 'Bhadohi', 'Cherthala', 'Madnapalle',
'Mokokchung', 'Pappadahandi', 'Lalitpur', 'Farrukhbad', 'Shahabad',
'Jalalabad', 'Tilhar', 'Garhshnker', 'Hajipur', 'Paranpur',
'Gauribidanur', 'Wankaner', 'Morbi', 'BariSadri', 'Neemuch',
'Sangareddy', 'Islampure', 'Nakhatrana', 'Chandauli', 'Dhrmsthala',
'Jowai', 'Chiraiyakot', 'Jiyanpur', 'Siwan', 'Rawatsar', 'Loharu',
'Kozhenchery', 'Printhlmna', 'Aliganj', 'Chhibramau', 'Taranagar',
'Khed', 'Mundakayam', 'Nimbahera', 'Sangola', 'Asifabad',
'Arambag', 'Berhampore', 'Manbazar', 'Shahganj', 'Azamgarh',
'Saraimeer', 'Neemrana', 'Barbil', 'Razole', 'Sultana', 'Budhana',
'Raiganj', 'Radhanpur', 'Moranhat', 'Khatra', 'Simlapal',
'Ghatkesar', 'Betnoti', 'Bongaon', 'Nedumangad', 'Karukachal',
'Soro', 'Kamarpukur', 'Keshiary', 'Contai', 'Manglamaro',
'Puranpur', 'Palakollu', 'Falna', 'Thirthahalli', 'Tarkeshwar',
'Hathras', 'Nipani', 'Kulithalai', 'Brajrajnagar', 'Sundargarh',
'Sambalpur', 'Jalore', 'Bhinmal', 'Bhilad', 'Pilibanga',
'Khanakul', 'Kothanalloor', 'Nirjuli', 'Sidhmukh', 'Kullu',
'Manteswar', 'Ranaghat', 'Gudalur', 'Kasganj', 'Helencha',
'Dabhoi', 'Balangir', 'Bargarh', 'Sirohi', 'Gondal', 'Morena',
'Nagpur', 'Baripada', 'Palitana', 'Samsi', 'Sumerpur', 'Vadipatti',
'Giddarbaha', 'Fazilka', 'Phusro', 'Tonk', 'SawaiMadhopur',
'Munger', 'Pauri', 'Sankerko', 'Nohar', 'Krishnanagar',
'Kuthuparamba', 'KharagpurBR', 'Jamui', 'DhrmpuriTS', 'Anuppur',
'Baruipur', 'Tirtol', 'Daurala', 'Jharsuguda', 'Central', 'Abohar',
'RampuraPhul', 'Hoshangabad', 'Cuttack', 'Kendrpara', 'Rajgarh',
'Durg', 'Balurghat', 'Chamorshi', 'Barasat', 'Gujiliam', 'Basta',
'Shahjhnpur', 'Tadipatri', 'Cuddapah', 'Badvel', 'Proddatur',
'Angul', 'Phulbani', 'Ambegaon', 'Chanchal', 'Malout',
'Uthangarai', 'Badlapur', 'Balugaon', 'Mahasamund', 'Badkulla',
'Kapadvanj'], dtype=object)
```

In [77]:
```
de['source_place'].unique()
```

Out[77]:
```
array(['Central_H_6', 'Trnsport_H', 'ChikaDPP_D', 'Veersagr_I',
       'Bilaspur_HB', 'Nelmngla_H', 'Hub', 'Dc', 'WrdN1DPP_D', 'Hospet',
       'Poonamallee', 'Porur_DPC', 'Chrompet_DPC', 'Layout PC',
       'Bagaluru_D', 'Central_D_12', 'Central_I_4', 'Lajpat_IP',
       'North_D_3', 'Balabhgarh_DPC', 'Central_DPP_3', 'MjgaonRd_D',
       'Shivaji_I', 'Shamshbd_H', 'KamaStrt_I', 'Xroad_D', 'Nehrugnj_I',
       'RazaviRd_D', 'KalyanNg_D', 'SindgiRD_D', 'Central_I_7',
       'VarunCly_DC', 'Central_H_1', 'Nangli_IP', 'North', 'VikasRam_D',
       'KndliDPP_D', 'MPward_D', 'Central_D_9', 'DavkharRd_D',
       'TgrniaRD_I', 'Central_D_1', 'JawanChk_D', 'SaiBansi_D',
       'NkshtrPz_D', 'YeolaRD_D', 'Bandel_D', 'DC', 'North_I_4',
       'RTCStand_D', 'PnukndRD_D', 'Central_DPP_1', 'KGAirprt_HB',
       'North_D_2', 'MROoffce_D', 'Athithnr_DC', 'RTOofice_D',
       'RjndraRd_D', 'Palani_D', 'DPC', 'ChowkDPP_D', 'Mthurard_L',
       'Mullanpr_DC', 'Mehmdpur_H', 'Mohali', 'Central_DPP_2',
       'RajCmplx_D', 'Vidyangr_D', 'Beliaghata_DPC', 'RjnaiDPP_D',
       'KaremDPP_D', 'AbbasNgr_I', 'Palwal', 'Mankoli_HB', 'Wardno3_D',
       'GreenVly_D', 'BhaRDDPP_D', 'Airport_H', 'Gateway_HB',
       'Tathawde_H', 'ChotiHvl_DC', 'PnjPiara_D', 'Kharar_DC',
       'Trmltmpl_D', 'AnugrDPP_D', 'Srirampt_D', 'GlbrgaRD_D',
       'DBRCmplx_D', 'Mainroad_D', 'OnkarDPP_D', 'KaranNGR_D',
       'Panchot_IP', 'Sohagpur_D', 'ChainDPP_D', 'Chrompet_L',
       'Busstand_D', 'JirgeNgr_D', 'BnsllNgr_D', 'Aswningr_I',
       'SivjiCWK_D', 'Central_I_1', 'KeranDPP_D', 'IndEstat_I', 'Court_D',
       'JmnvadRd_DC', 'NSTRoad_I', 'HydRoad_DC', 'Ragvendr_D',
       'Krishna_D', 'Nagaram_D', 'Rynapadu_H', 'BsstdDPP_D',
       'HawaiPlr_DC', 'Adhartal_IP', 'DumDum_DPC', 'Bomsndra_HB',
       'SsnRdDPP_D', 'Mamlatdr_DC', 'NCplxDPP_D', 'Swamylyt_D',
       'Narasipr_D', 'BrDbleRd_D', 'SulthnRd_D', 'NarsipuraRd_D',
       'Yadvgiri_IP', 'RatnaDPP_D', 'BegurRD_D', 'Thomas_D',
       'Central_D_2', 'TirupDPP_D', 'Gajuwaka_L', 'AtoNgrRd_I',
       'LaxmiNgr_D', 'NrdawDPP_D', 'Old City', 'Kundli_H', 'UdhamNgr_H',
       'Patelfli_D', 'Central_I_3', 'Vasanthm_I', 'KtsiGrsm_D',
       'ARBNorth_DC', 'Pngktgudi_D', 'Thalthru_DC', 'Bypasrd_D',
       'Sttyapar_D', 'Poonamallee_HB', 'VUNagar_DC', 'MotvdDPP_D',
       'NlgaonRd_D', 'Srnwsngr_D', 'Dakor_DC', 'Vaghasi_IP', 'Bnnrghta_L',
       'Thirumtr_IP', 'SelamRd_D', 'EastmnRD_D', 'VkotRoad_D',
       'GandhiRd_D', 'NJVNgr_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', 'SDKNgr_D', 'Bngisheb_D', 'TirupthiRd_D',
       'BljiMrkt_D', 'DataSagr_D', 'Govndsgr_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', 'Knrpati_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', 'MhpraRD_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', 'Mhdhvpur_D', 'Hillcard_DC',
       'WardNo3_D', 'Tiruchi', 'Sec 02_DPC', 'Sec-83_DC', 'Kadipur',
       'Chukhndi_D', 'HosptlRd_D', 'Tetultol_D', 'Wardno5_D',
       'HplrdDPP_D', 'Sracmplx_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', 'Mdiclcly_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',
       'Beleghta_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',
       'Bgwtichk_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', 'Kapshera_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', 'Enkndla_D', 'SrnvsNgr_D', 'RKComplx_D',
       'ShtDRDPP_D', 'VikrmMah_D', 'Rohtak', 'DvlalDPP_D', 'GainMrkt_L',
       'BsStdDPP_D', 'Darbhanga', 'Javahar_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',
       'NraynDPP_D', 'Nangli_L', 'Matriprm_IP', 'CCRoad_D', 'Subshngr_D',
       'BawliDPPP_D', 'Banjaria_D', 'PchpkrRD_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', 'KrshDPP_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', 'Shankrpa_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', 'Pnjbiyon_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', 'Nandrbar_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', 'goplpurm_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', 'Thvlrsrt_D', 'Palladam_DC',
'Bhabua_D', 'Torwa_DC', 'HousngBd_D', 'New Alipore_DPC',
'Mutyvila_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', 'RjndrNgr_DC', 'EtwahDPP_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',
'Kadtmpty_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', 'Srvdycwk_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', 'Chndrlpd_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', 'AzmrdDPP_D', 'Jamalpur_D',
'LNBRoad_D', 'Shop2DPP_D', 'DeVDPP_D', 'KSClny_DC', 'GagiDPP_D',
'HotelPrk_D', 'SnthiNGR_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',
'Shivprsad_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', 'Murtingr_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', 'Beltngdi_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',
'SuktDPP_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', 'RgstrOFC_D', 'Bhaluahi_D',
       'Thikiri_D', 'RajpurRD_D'], dtype=object)
```

In [78]:
```
de['source_state'].unique()
```

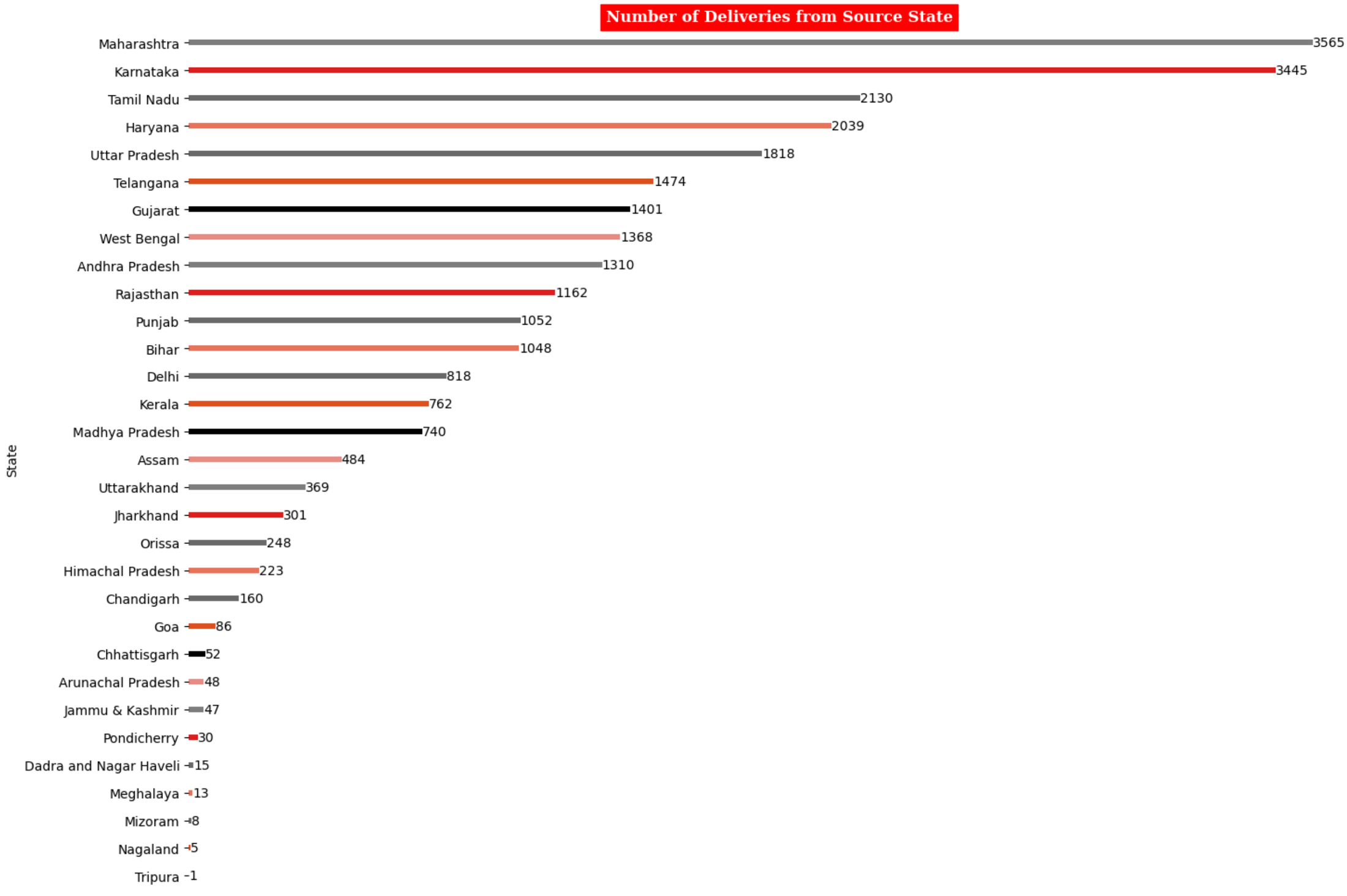
Out[78]:
```
array(['Uttar Pradesh', 'Madhya Pradesh', 'Karnataka', 'Haryana',
       'Maharashtra', 'Tamil Nadu', 'Gujarat', 'Delhi', 'Telangana',
       'Andhra Pradesh', 'Rajasthan', 'Assam', 'West Bengal', 'Punjab',
       'Chandigarh', 'Goa', 'Uttarakhand', 'Jharkhand', 'Pondicherry',
       'Orissa', 'Himachal Pradesh', 'Kerala', 'Arunachal Pradesh',
       'Bihar', 'Meghalaya', 'Chhattisgarh', 'Jammu & Kashmir',
       'Dadra and Nagar Haveli', 'Mizoram', 'Tripura', 'Nagaland'],
      dtype=object)
```

In [253…
```
de['source_state'].value_counts().to_frame().style.background_gradient(cmap='Reds')
```

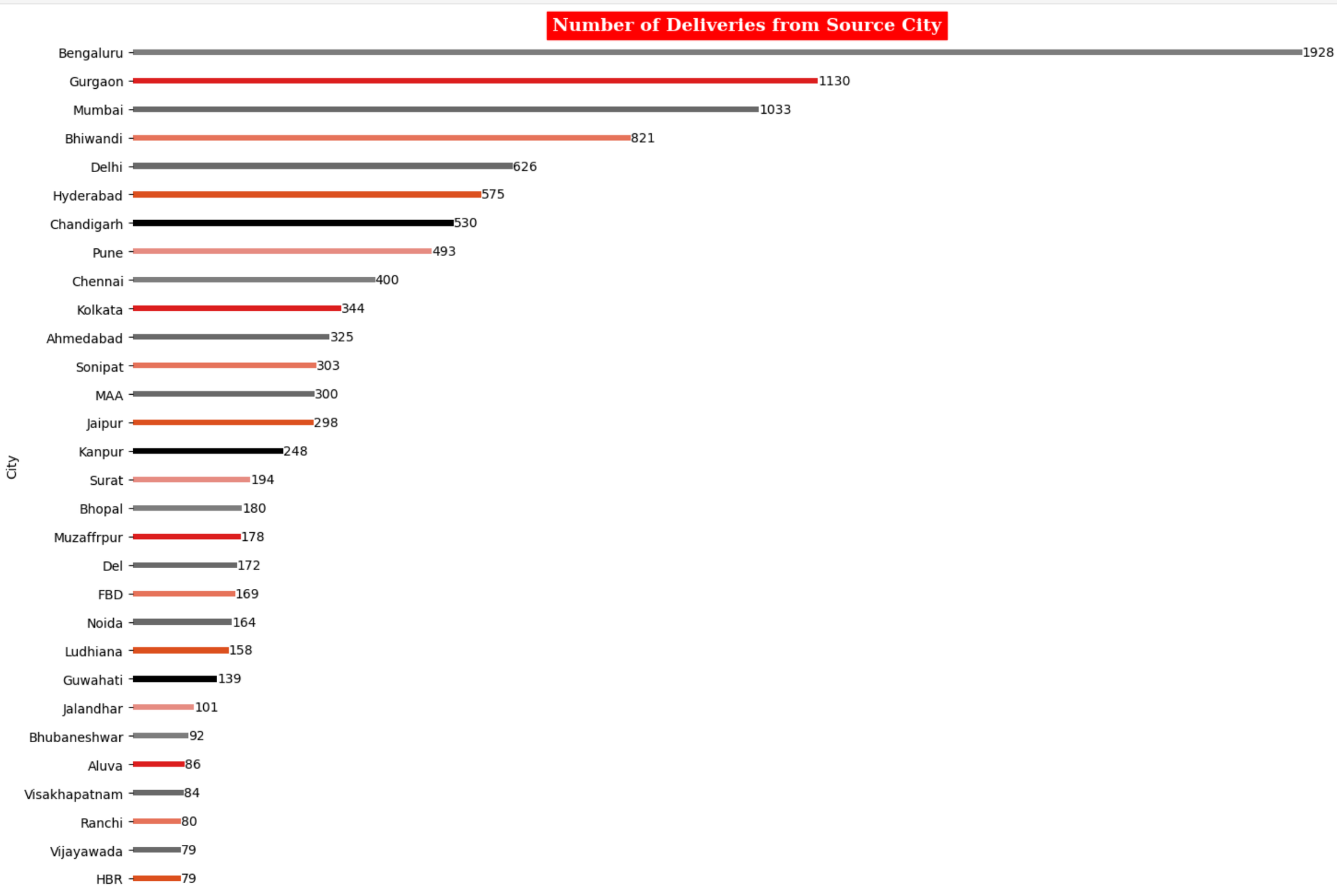
Out[253]:

source_state	count
Maharashtra	3565
Karnataka	3445
Tamil Nadu	2130
Haryana	2039
Uttar Pradesh	1818
Telangana	1474
Gujarat	1401
West Bengal	1368
Andhra Pradesh	1310
Rajasthan	1162
Punjab	1052
Bihar	1048
Delhi	818
Kerala	762
Madhya Pradesh	740
Assam	484
Uttarakhand	369
Jharkhand	301
Orissa	248
Himachal Pradesh	223
Chandigarh	160
Goa	86
Chhattisgarh	52
Arunachal Pradesh	48
Jammu & Kashmir	47
Pondicherry	30
Dadra and Nagar Haveli	15
Meghalaya	13
Mizoram	8
Nagaland	5
Tripura	1

In [80]:
```
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()
```



In [81]:
```
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.

In [82]:
```
de.describe().T
```

Out[82]:

	count	mean	min	25%	50%	75%	max	std
trip_creation_time	26222	2018-09-22 13:58:56.740969728	2018-09-12 00:00:16.535741	2018-09-17 03:57:50.900417024	2018-09-22 03:33:30.255023104	2018-09-27 19:55:17.273207040	2018-10-03 23:59:42.701692	NaN
od_start_time	26222	2018-09-22 17:49:54.012840448	2018-09-12 00:00:16.535741	2018-09-17 07:43:36.525784320	2018-09-22 07:17:15.379571712	2018-09-27 23:22:20.105725952	2018-10-06 04:27:23.392375	NaN
od_end_time	26222	2018-09-22 22:49:00.449498112	2018-09-12 00:50:10.814399	2018-09-17 15:10:35.615369472	2018-09-22 14:46:05.410478848	2018-09-28 03:19:50.211971840	2018-10-08 03:00:24.353479	NaN
start_scan_to_end_scan	26222.0	298.553375	20.0	90.0	152.0	307.0	7898.0	441.116974
actual_distance_to_destination	26222.0	92.533051	9.001351	21.65415	35.044329	65.557392	1927.447754	209.952652
actual_time	26222.0	200.92659	9.0	51.0	84.0	167.0	4532.0	385.728271
osrm_time	26222.0	90.785332	6.0	25.0	39.0	72.0	1686.0	185.558731
osrm_distance	26222.0	114.975334	9.0729	27.71915	43.54355	85.443949	2326.199219	254.426529
segment_actual_time	26222.0	199.095642	9.0	50.0	83.0	166.0	4504.0	382.145752
segment_osrm_time	26222.0	101.793343	6.0	25.0	42.0	79.0	1938.0	216.205933
segment_osrm_distance	26222.0	125.587128	9.0729	28.429099	45.797649	91.023573	2640.924805	286.6698
segment_actual_time_sum	26222.0	199.095642	9.0	50.0	83.0	166.0	4504.0	382.145752
segment_osrm_time_sum	26222.0	101.793343	6.0	25.0	42.0	79.0	1938.0	216.205933
segment_osrm_distance_sum	26222.0	125.587128	9.0729	28.429099	45.797649	91.023573	2640.924805	286.6698
od_total_time	26222	0 days 04:59:06.436657725	0 days 00:20:42.168787	0 days 01:30:58.665517750	0 days 02:32:20.203949500	0 days 05:07:17.158769	5 days 11:38:33.117274	0 days 07:21:14.957234047
od_time_diff_hour	26222.0	4.985121	0.345047	1.516296	2.538946	5.121433	131.642533	7.354155

In [83]:
```
de.describe(include='object').T
```

Out[83]:

	count	unique	top	freq
segment_key	26222	26222	trip-153671041653548748+IND209304AAA+IND000000ACB	1
trip_uuid	26222	14787	trip-153717306559016761	8
source_name	26222	1496	Gurgaon_Bilaspur_HB (Haryana)	1052
destination_name	26222	1466	Gurgaon_Bilaspur_HB (Haryana)	928
source_city	26222	1239	Bengaluru	1928
source_place	26222	1246	Bilaspur_HB	1052
source_state	26222	31	Maharashtra	3565
destination_city	26222	1236	Bengaluru	1863
destination_place	26222	1217	Bilaspur_HB	928
destination_state	26222	32	Karnataka	3497

In [84]:
```
de['destination_city'].unique()
```

Out[84]:
```
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', 'Oddnchtram', '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', 'Choutuppal', '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', 'Nagapttinm', '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', 'Mandya', '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', 'Kurukshetra', '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',
       'Wanaparthy', 'JoguGadwal', 'Modinagar', 'Meerut', 'Saharsa',
       'Triveninganj', 'Supaul', 'Madhepura', 'Araria', 'Raniganj',
       'Simrahi', 'Sheohar', 'Pupri', 'Sitamari', 'Srisailam', 'Nandyal',
       'Bngnpalle', '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', 'Balaghat', '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',
       'Khambhalia', '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',
       'Ghatampur', 'Mangrol', 'Veraval', 'Fatehpur', 'Mahoba', 'Banda',
       'Pukhrayan', 'Orai', 'Konch', 'Jamjodhpur', 'Mejia', 'Rghunthpur',
       'Duliajan', 'Dibrugarh', 'Digboi', 'Mussoorie', 'Tarkeshwar',
       'Kalpetta', 'Pokhran', 'Phalodi', 'Rewa', 'Sidhi', 'Bilimora',
       'Bolpur', 'Guskhara', 'Nanoor', 'Mathabhang', 'CoochBehar',
       'Dinhata', 'Kathua', 'Samba', 'Raver', 'Jalgaon', 'Narsinghgarh',
       'Pachore', 'Vapi', 'Hyd', 'Barpeta', 'Sholinghur', 'Talegaon',
       'Rajgurunagar', 'Jairampur', 'Kittur', 'Karnaprayag', 'Tangi',
       'Dhemaji', 'Shillong', 'Bailhongal', 'Chomu', 'Sikar', 'Balrampur',
       'Tulsipur', 'Gonda', 'Melur', 'Chittaurgarh', 'Kavali', 'Banswara',
       'Ghosi', 'Achrol', 'Paota', 'Jehanabad', 'Edappal', 'Guruvayoor',
       'Attur', 'Chetpet', 'Arani', 'Polur', 'Khandala', 'Wai', 'Loharu',
       'Uchila', 'Kundapura', 'Bhatkal', 'Honnavar', 'Kumta', 'Ankola',
       'Dhrmsthala', 'Karkala', 'Tumkur', 'Kottayam', 'Alappuzha',
```

```
'Koyilandy', 'Kallachi', 'Vadakara', 'Kuthuparamba', 'Mylduthuri',
'Mannargudi', 'Thirukkatupli', 'Muthukulathur', 'Narikkudi',
'Coonoor', 'Gudalur', 'Mahabubnagar', 'Bijnapally', 'Jadcherla',
'Peravurani', 'Karaikudi', 'Aranthangi', 'Pudukkotti',
'Ponnamaravathi', 'Badarpur', 'Betamcherla', 'Kulithalai',
'Perambalur', 'Thuraiyur', 'Ariyalur', 'Jayamkondan', 'Lalpet',
'Karwar', 'Kalka', 'Forbesganj', 'Narpatganj', 'Sivakasi',
'Maharajapuram', 'Sankaran', 'Rajpalayam', 'Gobicheti',
'Anthiyour', 'Jaora', 'Nabha', 'Malerkotla', 'Kattappana', 'Rehli',
'Bina', 'HanumanJNC', 'Vuyyuru', 'Madikeri', 'Koppa',
'Ramanathapura', 'Razole', 'Amalapuram', 'Kherli', 'Kolar',
'Mulbagal', 'Chintamani', 'Bangarapet', 'Bethamangala',
'Udumalpet', 'Pollachi', 'Ukkadagatri', 'Khandela', 'Pilibhit',
'Baghpat', 'Chakia', 'Kangayam', 'Tirpur', 'Dharapuram', 'Dinara',
'Champa', 'Bansi', 'Kanchipuram', 'Arakkonam', 'Fatepur',
'Nedumangad', 'Malemruvathur', 'Yellandu', 'Rayaparthi', 'Vallior',
'Nagarcoil', 'Tirunelveli', 'Amreli', 'Eral', 'Peikulam',
'Thisayanvilai', 'Tirchchndr', 'Kodad', 'Kusumnchi', 'Sahebganj',
'Deoghar', 'Jamtara', 'Parkal', 'Mulugu', 'Mahadevpur',
'Bhupalpally', 'Sullia', 'Krishnagiri', 'Husnabad', 'Narsinghpur',
'Ramagundam', 'SikandraRao', 'Etah', 'Jalesar', 'Ghaziabad',
'Navsari', 'Valsad', 'Haldwani', 'Gauribidanur', 'Bagepalli',
'Chabua', 'Chhaygaon', 'Sivaganga', 'Manamelkudi', 'Oriyur',
'Thiruvadanai', 'Saraiya', 'Satana', 'Malegaon', 'Manmad',
'Siruguppa', 'Asangaon', 'Bhuvanagiri', 'Mothkur', 'Central',
'Mahasamund', 'Chandpur', 'Patan', 'Madakasira', 'Salem',
'Bamangola', 'Balipara', 'Jassur', 'Jammu', 'Sehore', 'Ashta',
'Perundurai', 'Marakkanam', 'Bhusawal', 'Mau', 'Betnoti',
'Balasore', 'Tarnau', 'Didwana', 'Bantwal', 'Rajsamand', 'Jangaon',
'JhumriTlya', 'Gopalganj', 'Shimoga', 'Tikamgarh', 'Panna',
'Jhabua', 'Trivandrum', 'Faridpur', 'Shirur', 'Mokokchung', 'Tuni',
'Kakinada', 'Nabarangpr', 'Jeypore', 'Rameswram', 'Ramnthpurm',
'Paramakudi', 'Nasirabad', 'Kekri', 'Bilara', 'Badnaur',
'Patancheru', 'Shoranur', 'Pazhayannur', 'Sankaramangalam',
'Buldhana', 'Chikhli', 'Fatehabad', 'Cumbum', 'Sakleshpur',
'Nagamangala', 'Sathyamangalam', 'Ooty', 'HazratJandaha',
'Machhiwara', 'Khurai', 'Malur', 'Lonavala', 'Baraut', 'Avinashi',
'Jhunjhunu', 'Shrimadhopur', 'Sultana', 'NeemKaThana', 'DehriSone',
'Bhind', 'Bijnor', 'Madhupur', 'Bhavnagar', 'Shindkheda',
'Jammikunta', 'Sangareddy', 'Manvi', 'Sindhanur', 'Raipur',
'Vemulawada', 'Kaghaznagar', 'Asifabad', 'Manthani', 'Chinnur',
'Basti', 'Gangarmpur', 'Panagarh', 'Nanjangud', 'Gundlupet',
'Thirumalagiri', 'Seoni', 'Chhindwara', 'Lakhnadon', 'Hansi',
'Bobbili', 'Soraon', 'Phulpur', 'Maihar', 'Churhat', 'Anupgarh',
'Srivijaynagar', 'Dharmapuri', 'Kokrajhar', 'Bongaigaon',
'Ghanpur', 'Chopan', 'Markapur', 'Vinukonda', 'North', 'Bikaner',
'Nagaur', 'Sujangarh', 'Challakere', 'Molakalmuru', 'Udupi',
'Satara', 'Joda', 'Narnaul', 'Nandigama', 'Nipani', 'Nohar',
'Sidhmukh', 'Malappuram', 'Printhlmna', 'Katwa', 'Bareilly',
'Benipatti', 'Dighwara', 'Karnal', 'Sangrur', 'Bariya', 'Budhana',
'Barhi', 'Rath', 'Sujanpur', 'Shahdol', 'Anakapalle', 'Narsiptnm',
'Golaghat', 'Bishwanath', 'Ranipet', 'Kalpakkam', 'Jiyanpur',
'Dohrighat', 'Mangaldoi', 'Dhekiajuli', 'Reengus', 'Nokha',
'Peterbar', 'Hazaribag', 'Ramgarh', 'Mandapeta', 'Shadnagar',
'Vikarabad', 'Tandur', 'Kotagiri', 'Narsingpur', 'Nandikotkr',
'Mandla', 'Palampur', 'Kangra', 'DehraGopipur', 'Pangodu',
'Pappadahandi', 'Anuppur', 'PaliBirsighpr', 'Rajgarh', 'Rajkot',
'Tenkasi', 'Ambasamdrm', 'Mohania', 'Bheemunipatnam',
'Vizianagaram', 'Kasaragod', 'Moodbidri', 'Anandnagar',
'Maharajganj', 'Nichlaul', 'RaisingNgr', 'Jaisalmer', 'Barmer',
'GanjBasoda', 'Sagar', 'Akhnoor', 'Piparcity', 'Tura', 'Jaunpur',
'Jalalpur', 'Pratapgarh', 'Cochin', 'Arimbur', 'Khanapur',
'Irinjlkuda', 'Chalakudy', 'Jath', 'Padrauna', 'Theni', 'Mudigere',
'Barwala', 'Chaksu', 'Chimkurthy', 'Giridih', 'DoomDooma',
'Tinusukia', 'Namsai', 'Tezu', 'Islampure', 'Dharmanagr',
'Agartala', 'Chandauli', 'Manthuka', 'Karungaply', 'Champhai',
'Aizawl', 'Kozhikode', 'Kunnathund', 'Paithan', 'Georai',
'Shevgaon', 'Beed', 'Koraput', 'Atmakur', 'Dhone', 'Teok',
'Mariani', 'Arsikere', 'Areacode', 'Eluru', 'SirhindFatehgarh',
'Bikramgang', 'Bellmpalli', 'Raiganj', 'Kaliyaganj', 'Paranpur',
'Sihora', 'Shivpuri', 'Gondal', 'Khurja', 'Tonk', 'Parbhani',
'Suratgarh', 'Mandsaur', 'Sitamau', 'Agra', 'Amalner', 'Pachora',
'Erandol', 'Pataudi', 'LakhimpurN', 'Gopiganj', 'Baripada',
'MughalSarai', 'Palamaner', 'Umerkote', 'Shamshabad', 'Dhuri',
'Farrukhbad', 'Shahabad', 'Shahjhnpur', 'Aliganj', 'Jalalabad',
'Palakollu', 'Samsi', 'Wankaner', 'BariSadri', 'Pilibanga',
'Vishakhapatnam', 'Lodhan', 'Hoshangabad', 'Bokakhat', 'Moranhat',
'Anjar', 'Barauni', 'Gahmar', 'Jowai', 'Varanasi', 'Chiraiyakot',
'ChrkhiDdri', 'Kozhenchery', 'Chhibramau', 'Karukachal',
'Parakkdavu', 'Nimbahera', 'Neemuch', 'MirzapurWB', 'Berhampore',
'Manbazar', 'Khatra', 'Kothanalloor', 'Badlapur', 'Saraimeer',
'Shahganj', 'Kerala', 'Buhana', 'Tallada', 'Itahar', 'Manikchak',
'Sonari', 'Balotra', 'Simlapal', 'Ghatkesar', 'Helencha',
'Jaleswar', 'Soro', 'Manglamaro', 'Keshiary', 'Contai', 'Howrah',
'Udala', 'Chikmagalur', 'Kasganj', 'Umaria', 'MarwarJn', 'Jalore',
'Thirthahalli', 'Khanakul', 'Chikodi', 'Khamgaon', 'Sundargarh',
'Rajgangpur', 'Bargarh', 'Bhinmal', 'Sirohi', 'Dabhoi',
'RampuraPhul', 'Bhilad', 'Arambag', 'Vaikom', 'Manteswar',
'Nabadwip', 'Gangarampr', 'Bongaon', 'Morena', 'Peddapalli',
'Roing', 'Fazilka', 'Cjb', 'Sonepur', 'Sambalpur', 'Balangir',
'Sumerpur', 'Jasdan', 'Khalilabad', 'Nagpur', 'Aunrihar',
'Mungaoli', 'Chanchal', 'Falna', 'Gujiliam', 'Malout', 'Gomoh',
'Kamarpukur', 'AmaDubi', 'Azamgarh', 'Phusro', 'Tirurangadi',
'SawaiMadhopur', 'Sultanganj', 'Giddarbaha', 'Bhadra', 'Hanskhali',
'Munger', 'KharagpurBR', 'Baruipur', 'Khatauli', 'Ambegaon',
'Abohar', 'Nirsa', 'Itarsi', 'Cuttack', 'Taranagar', 'Kanker',
'Luxettipet', 'Basta', 'Bhadohi', 'Tilhar', 'Tadipatri',
'Proddatur', 'Badvel', 'Cuddapah', 'Angul', 'Phulbani', 'Khetri',
'Daman', 'Uthangarai', 'Durg', 'Thachnttukra', 'Krishnanagar',
'Ranaghat', 'Kapadvanj', 'Lunawada'], dtype=object)
```

In [85]:
```
de['destination_place'].unique()
```

Out[85]:
```
array(['Bilaspur_HB', 'Central_H_6', 'ShntiSgr_D', 'ChikaDPP_D',
       'Mehmdpur_H', 'MiraRd_IP', 'Hospet', 'Dc', 'WrdN1DPP_D',
       'Sriperumbudur_Dc', 'Poonamallee', 'Vandalur_Dc', 'NwYlhnka_DC',
       'Layout PC', 'Central_I_4', 'Central_D_3', 'Bhogal',
       'Rahatani DPC', 'Faridabad', 'Shivaji_I', 'Central_DPP_3',
       'MjgaonRd_D', 'KamaStrt_I', 'Nelmngla_H', 'Uppal_I', 'KalyanNg_D',
       'Nehrugnj_I', 'SindgiRD_D', 'RazaviRd_D', 'Bhankrot_DC',
       'Central_I_7', 'Central_I_2', 'Janakpuri', 'Hub', 'VikasRam_D',
       'MPward_D', 'SourvDPP_D', 'Varachha_DC', 'SaiBansi_D',
       'Central_D_1', 'JawanChk_D', 'DavkharRd_D', 'NkshtrPz_D',
       'YeolaRD_D', 'TgrniaRD_I', 'North_I_4', 'Bandel_D', 'DC',
       'PnukndRD_D', 'Gokulam_D', 'Babupaty_D', 'Bomsndra_HB',
       'MROoffce_D', 'Alwal_I', 'Palani_D', 'RTOofice_D', 'lalaNGR_D',
       'Athithnr_DC', 'RjndraRd_D', 'ChowkDPP_D', 'DPC', 'Mohali',
       'Mullanpr_DC', 'Sanpada_I', 'JajuDPP_D', 'Vidyangr_D',
       'Central_DPP_2', 'Dankuni_HB', 'KaremDPP_D', 'Wagodha_D',
       'Shamshbd_H', 'AbbasNgr_I', 'Palwal', 'Balabhgarh_DPC',
       'Wardno3_D', 'GreenVly_D', 'BhaRDDPP_D', 'Mankoli_HB',
       'SnkunDPP_D', 'PnjPiara_D', 'ChotiHvl_DC', 'Kharar_DC', 'Darbe_DC',
       'AnugrDPP_D', 'GlbrgaRD_D', 'DBRCmplx_D', 'Mainroad_D',
       'Ward2DPP_D', 'MilrGanj_HB', 'East_H_1', 'KaranNGR_D',
       'ChainDPP_D', 'Adhartal_IP', 'Poonamallee_HB', 'JirgeNgr_D',
       'BnsllNgr_D', 'Tathawde_H', 'SivjiCWK_D', 'Busstand_D',
       'Central_DPP_1', 'StnRdDPP_D', 'BhowmDPP_D', 'Samrvrni_D',
       'JmnvadRd_DC', 'AdrshSt_DC', 'Nagaram_D', 'Krishna_D',
       'Rynapadu_H', 'HydRoad_DC', 'Ragvendr_D', 'NSTRoad_I',
       'BsstdDPP_D', 'HawaiPlr_DC', 'Panchot_IP', 'Bargawan_DC',
       'KGAirprt_HB', 'keshod_DC', 'NCplxDPP_D', 'SsnRdDPP_D',
       'Mamlatdr_DC', 'BrDbleRd_D', 'Yadvgiri_IP', 'NarsipuraRd_D',
       'Narasipr_D', 'SulthnRd_D', 'Jogeshwri_L', 'JublieRD_D',
       'Thomas_D', 'BegurRD_D', 'TirupDPP_D', 'Santalpr_D', 'AtoNgrRd_I',
       'Gajuwaka_IP', 'LaxmiNgr_D', 'NrdawDPP_D', 'Trnsport_H',
       'Central_H_1', 'UdhamNgr_H', 'Kundli_H', 'Patelfli_D',
       'Rohini_DPC', 'KtsiGrsm_D', 'ARBNorth_DC', 'Pngktgudi_D',
       'Thalthru_DC', 'Sttyapar_D', 'Vasanthm_I', 'Bypasrd_D',
       'Mohan_Nagar_DPC', 'Madhavaram_L', 'MotvdDPP_D', 'Vaghasi_IP',
       'NlgaonRd_D', 'Srnwsngr_D', 'Aswningr_I', 'Sec 02_DPC', 'Dakor_DC',
       'GandhiRd_D', 'EastmnRD_D', 'VkotRoad_D', 'Thirumtr_IP',
       'NJVNgr_D', 'SelamRd_D', 'GMukrDPP_D', 'GariDPP_D', 'Central_I_1',
       'MP Nagar', 'Phaphamu_DC', 'Porur_DPC', 'Perungudi_DPC',
       'AkhirDPP_D', 'GModDPP_D', 'IndstlAr_I', 'Raiprvlg_L', 'Jhilmil_L',
       'Central_D_2', 'KoilStrt_D', 'Haridwar', 'Nzbadrd_D', 'Xroad_D',
       'Devenply_I', 'SuryaDPP_D', 'Dwaraka_D', 'Menagrdn_D', 'JKRoad_D',
       'Mayapuri_PC', 'Hoodi_IP', 'NvygRDPP_D', 'CrossRD_D', 'PhrmPlza_D',
       'Banikatt_D', 'Sulgwan_D', 'Indsarea_D', 'Dhelu_D', 'UBamdDPP_D',
       'AchneraRD_D', 'JPNagar_Pc', 'KHRoad_I', 'Maheva_D', 'Chowk_D',
       'BkgnRoad_D', 'TahsilRD_D', 'Kishangarh_DPC', 'Kuntikna_H',
       'CharRsta_D', 'CottonGreen_DPC', 'CikhliRD_D', 'PunjabiB_L',
       'Kengeri_IP', 'Indira Nagar', 'Peenya_IP', 'Sirikona_H',
       'Khandeshwar_Dc', 'ClgRDDPP_D', 'Alwal_L', 'StatonRD_D',
       'Pashan DPC', 'CP', 'KetyDPP_D', 'OstwlEmp_D', 'BaljiDPP_D',
       'Khenewa_D', 'Mhbhirab_D', 'RSRoad_D', 'Balajicly_I', 'Artmclny_D',
       'MGRoad_D', 'SDKNgr_D', 'TirupthiRd_D', 'Bngisheb_D', 'Sector63_L',
       'DataSagr_D', 'Govndsgr_D', 'BljiMrkt_D', 'Bnnrghta_L',
       'Beliaghata_DPC', 'Airport_H', 'Lake Avenue_DPC', 'East',
       'Memnagar', 'Mumbra_DC', 'Satellite', 'Pakrela_D', 'Auliyapr_D',
       'Ulhasngr_DC', 'Pawane_L', 'Kalyan West _Dc', 'Bbganj_I',
       'Central_H_2', 'Mthurard_L', 'New Alipore_DPC', 'RPC', 'Peenya_L',
       'Lovely_D', 'Mataward_D', 'PatelWrd_D', 'Kappalur_H',
       'Central_D_12', 'Rkcomplx_DC', 'Erode', 'Chrompet_L',
       'Central_D_9', 'KhirByps_I', 'Agraroad_I', 'Katrmira_D',
       'Sudmpuri_D', 'Jaipur', 'Chrompet_DPC', 'SamathBv_D', 'ward9_D',
       'Kuslpram_I', 'VadaiDPP_D', 'HudcoDPP_D', 'Ward14_D', 'AmvdiDPP_D',
       'Nalasopara', 'Sixmile', 'Chandmari', 'Sardala_D', 'VarunCly_DC',
       'Banikhet_D', 'Bangotu_D', 'Chuanpur_I', 'RatanDPP_D',
       'krshnPly_DC', 'BllvMarg_D', 'Central_D_10', 'AstrdDPP_D',
       'MhpraRD_D', 'NgrNigam_DC', 'Egmore_DPC', 'Nangli_IP',
       'Vadgaon Sheri DPC', 'Karayam_H', 'JNPT_D', 'Lajpat_IP',
       'Madhavaram_DPC', 'Mhdhvpur_D', 'RTOroad_D', 'ABPath_D',
       'Hillcard_DC', 'Samyaprm_D', 'Sec-83_DC', 'Blbgarh_DC', 'Manesar',
       'ICDCant_D', 'B_RPC', 'HosptlRd_D', 'Bhgtpura_D', 'Wardno5_D',
       'WrdN4DPP_D', 'Tetultol_D', 'GndhiNgr_IP', 'FoySGRRD_I',
       'Nayagaon_I', 'Basni_I', 'DKLogDPP_D', 'JawaharN_D', 'RoshnBgh_I',
       'SamitiRd_D', 'Kundli_P', 'TrtllaRD_L', 'GtRoad_D', 'RjghatRd_D',
       'HrihrNgr_I', 'TownDPP_D', 'Madaprum_D', 'Thmpulam_D',
       'Kalynpur_I', 'Bypassrd_D', 'HnumnDPP_D', 'Raghogrh_D', 'StRoad_D',
       'Pandrnga_I', 'CivilHPL_D', 'Srikot_D', 'CGRoad_D', 'WageDPP_D',
       'Hejunagr_D', 'MissonRd_D', 'JangiRd_D', 'Kaithwal_D',
       'Bsavangr_D', 'Adargchi_IP', 'Jogshwri_I', 'GndhiNGR_D',
       'Cdosclrd_D', 'GadagRD_D', 'Sector4_D', 'Govind_D', 'Parasi_D',
       'Waidhan_D', 'Ward8DPP_D', 'ArtoDPP_D', 'Panipat', 'Khajuria_I',
       'SriRmNGR_D', 'GuttalRD_D', 'Mangri_I', 'Sector1A_IP',
       'Shamshbd_P', 'Dankuni_P', 'Markndpr_D', 'Udyabata_D',
       'Kapleswr_D', 'Okhla_PC', 'Nangli_L', 'Kakdepot_D', 'Kurduwdi_D',
       'Oilmilrd_D', 'Tiglgndi_D', 'LICOffce_D', 'SubhVRTL_I', 'HUB',
       'Patparganj_DPC', 'Chndivli_PC', 'KSClny_DC', 'Vidygiri_D',
       'Vardhard_D', 'Mankoli_GW', 'Chrompet_PC', 'Bilaspur_P',
       'Pandesra_Gateway', 'MhmodNgr_D', 'Dehradun', 'Ramvlg_D',
       'HnmntNgr_D', 'SH78_D', 'Soghra_D', 'PnditNGR_D', 'ChndrNgr_D',
       'Robinson_D', 'Poothole_D', 'VaniThtr_D', 'IOTCEncl_L',
       'Tolichwk_I', 'Central_I_3', 'Karelibaug_DPC', 'Bgwtichk_D',
       'BypassRD_D', 'Kapshera_L', 'RIICO_L', 'Koliplm_I', 'Sirjudin_D',
       'PunjbiPd_D', 'Sarubali_D', 'YuktiDPP_D', 'Rcocmplx_D',
       'AnprnDPP_D', 'Nagar_DC', 'Katira_D', 'Rozapar_D', 'Jantaclg_D',
       'Diakkawn_D', 'Bankura_D', 'Salanpur_D', 'Talkui_D', 'BhgyaNgr_D',
       'ZebaTWR_D', 'North_R_8', 'Aurangabad', 'NagarDPP_D', 'MaxDPP_D',
       'BtaiRoad_D', 'Kollgpra_D', 'ShivmDPP_D', 'MhrjaDPP_D',
       'WdN14DPP_D', 'Ward17_D', 'Atapaka_D', 'GvrCompx_D', 'ArhamDPP_D',
       'GndhiDPP_D', 'PeroorRD_D', 'DindiRD_D', 'VidyaNGR_D',
       'Mundhawa_L', 'BoiDPP_D', 'SrifoDPP_D', 'Kntgorya_D', 'NditaDPP_D',
       'DohalDPP_D', 'GopalDPP_D', 'KrsprDPP_D', 'UtBzrDPP_D',
       'SavtaHTL_D', 'Hindcwk_D', 'GrmNgriya_D', 'HoliCDPP_D',
       'MdothdRD_D', 'kalibari_D', 'Alngjuri_D', 'RicMilRd_D',
       'Bhogpur_D', 'AkhraBzr_D', 'PlaceCol_D', 'TahurDPP_D',
       'Anaipeta_D', 'Bardivan_D', 'Wardno6_D', 'ByePass_D', 'MohanPrk_D',
       'SChwkDPP_D', 'SagarDPP_D', 'Gaurkshn_I', 'LxmiNiws_D', 'Mundhe_D',
       'Mahad_D', 'Shantanu_D', 'LSRoad_DC', 'VallaDPP_D', 'ColctrOf_D',
       'SikriKla_DC', 'Meerut', 'Wazirpur_L', 'Gangjala_D', 'SadrHsptl_D',
       'Krishnpr_D', 'Wardn13_D', 'Bazar_D', 'Ward9DPP_D', 'SngihiRD_D',
       'Durma_D', 'Sishumdr_D', 'SrnvsNgr_D', 'Enkndla_D', 'YTRd_D',
       'ShtDRDPP_D', 'RKComplx_D', 'VikrmMah_D', 'KirtiNgr_D',
       'DvlalDPP_D', 'Rohtak', 'Patiala', 'GainMrkt_L', 'Darbhanga',
       'Javahar_D', 'Nagar_D', 'MuruPost_D', 'patna_D', 'GodamDPP_D',
       'Vijayght_D', 'Shyndco_D', 'AgrohDPP_D', 'SchdvDPP_D', 'SaiNgr_D',
       'GVManu_D', 'Madnpali_D', 'RTCStand_D', 'Gurudwar_D', 'AjmhwDPP_D',
       'BhukrdPP_D', 'Mwalibad_D', 'MithmdRd_D', 'Subhash_D',
       'Sookhtal_D', 'Kumud_D', 'SuzkiSrv_D', 'PushPlza_D', 'NraynDPP_D',
       'LalBagh_D', 'CCRoad_D', 'Banjaria_D', 'Matriprm_IP', 'Subshngr_D',
       'KasyaDPP_D', 'East_I_21', 'BypassRd_D', 'PchpkrRD_D',
       'Panderia_D', 'TrnsptNGR_D', 'Hatpada_D', 'Dudhani_D', 'Bhaleti_D',
       'BpassDPP_D', 'Ward6_D', 'Fathuluh_D', 'KotdwrRD_D', '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',
```

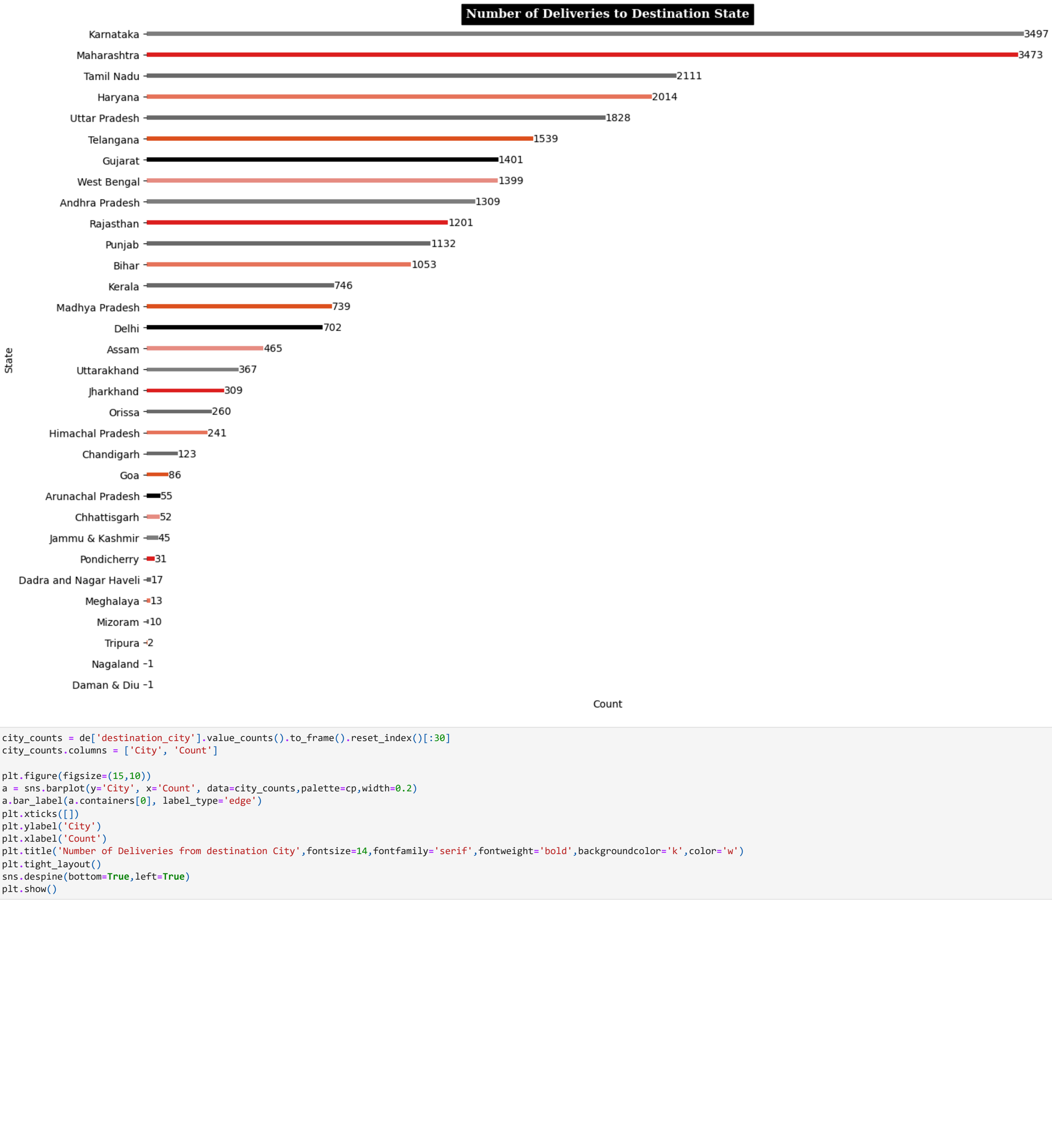
'GTRoad_D', 'SJRoad_D', 'Kanongyn_D', 'DcntCLY_D', 'Arlumodu_D',
'Mutyvila_D', 'MhraChng_D', 'AryaNagr_D', 'Kharghar_D',
'NdiaTola_D', 'Pbroad_DC', 'ZuariNgr_IP', 'Goa', 'HapurRD_D',
'Swargash_D', 'WardNo4_D', 'Haripur_D', 'KamnHbRD_I', 'GunjRDPP_D',
'Aravind_D', 'HanumDPP_D', 'Hitech_D', 'TKRoad_D', 'Kumrpurm_D',
'MunplDPP_D', 'Gobindgarh_DC', 'Town_D', 'Amankovl_D',
'Klskhrpt_D', 'PostofJN_D', 'KrantiNgr_D', 'MIDCAvdn_I',
'DhuleRd_D', 'DhuleRoad_D', 'Nandrbar_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', 'Itachnda_D',
'Pshimpra_D', 'Psthrjhr_D', 'BOB_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',
'Beltngdi_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', 'Kmrajngr_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',
'Srvdycwk_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', 'Thvlrsrt_D',
'Palladam_DC', 'Techrcly_D', 'Wardno7_D', 'Brplicwk_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', 'Shnmgprm_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', 'KndliDPP_D',
'Pdmavati_D', 'JydevNGR_D', 'CivlLine_D', 'ChngiDPP_D',
'RjndrNgr_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',
'ThanaDPP_D', 'Salem', 'PC', 'EragnDPP_D', 'Antop Hill',
'AadiDPP_D', 'TrnptNgr_L', 'Trimulgherry_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',
'Kdthdstrt_D', 'TnhbBlkC_D', 'VagaiNgr_D', 'LxmntDPP_D',
'BhmrdDPP_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', 'Chndrlpd_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', 'Sholinganallur_Dc', 'MdhsnDPP_D', 'Kadipur',
'Kothuru_D', 'Wardno8_D', 'BaruaRd_D', 'Potheri', 'ChrliDPP_D',
'Chatrpr_DC', 'MBTRd_DC', 'Sadras_D', 'AzmrdDPP_D', 'LNBRoad_D',
'Shop2DPP_D', 'DeVDPP_D', 'GagiDPP_D', 'BodomBzr_DC', 'HotelPrk_D',
'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', 'Sracmplx_D', 'Katghara_D',
'Mhimapur_D', 'Nimachrd_D', 'Kdvantra_D', 'Chtrpuza_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', 'Bhainpura_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',
'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', 'EtwahDPP_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', 'RgstrOFC_D',
       'Sanpada_CP', 'Bhilai_DC', 'Nattukal_D', 'AnadiDPP_D',
       'ArickDPP_D', 'VrdhriRD_D'], dtype=object)
```

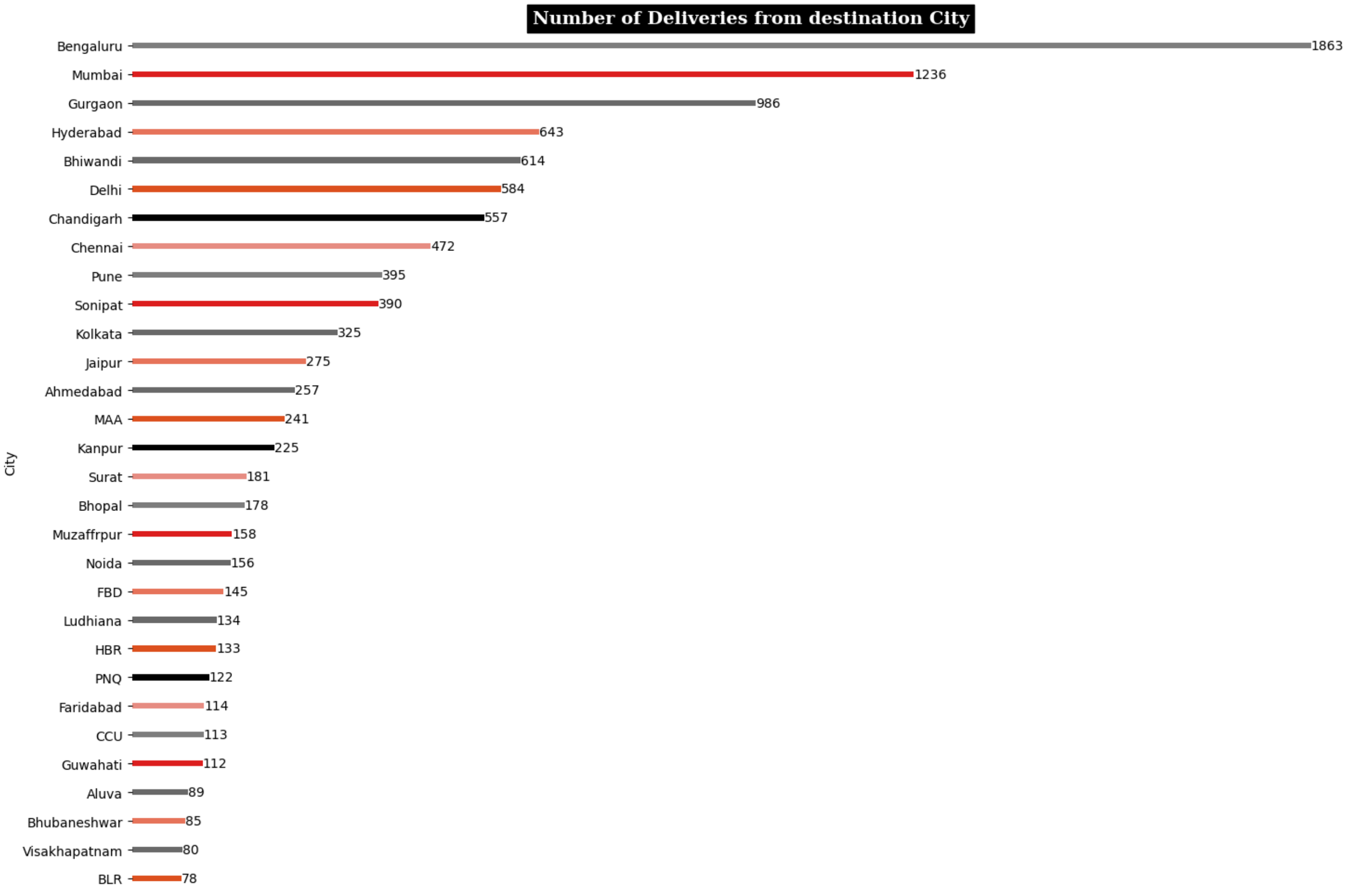
In [86]:
```
de['destination_state'].unique()
```

Out[86]:
```
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)
```

In [87]:
```
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='k',color='w')
plt.tight_layout()
sns.despine(bottom=True,left=True)
plt.show()
```



In [88]:
```
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`

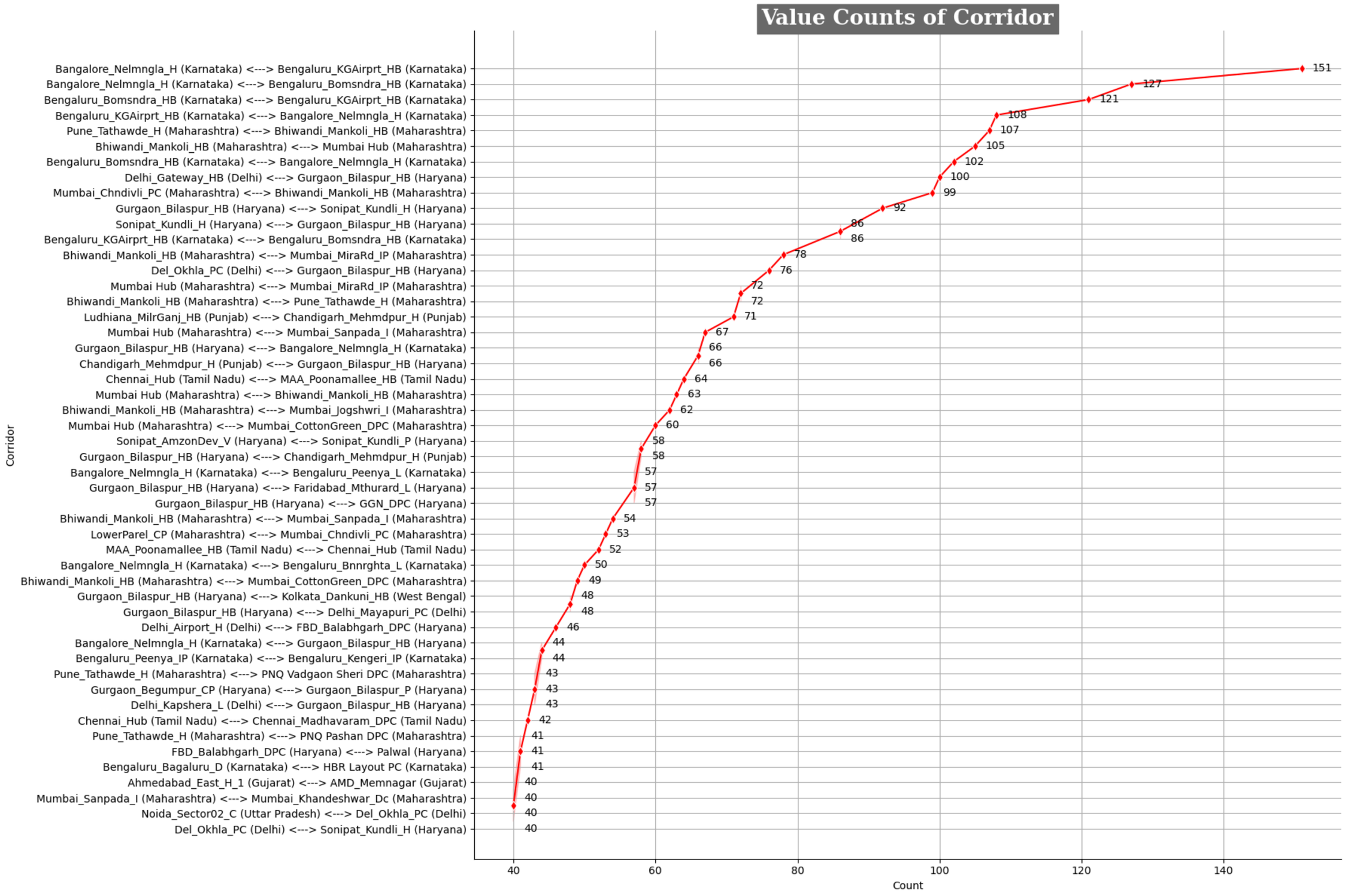
- Cities like **Bengaluru**, **Mumbai**, **Gurgaon**, **Bhiwandi**, **Hyderabad**, **Delhi** where the major no.of booking are received.

In [89]:
```
np.set_printoptions(threshold=np.inf)
```

In [90]:
```
de['corridor'] = de['source_name'] +' <---> '+ de['destination_name']
de['corridor'].value_counts()
```

Out[90]:
```
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
```

In [91]:
```
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',backgroundcolor='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:

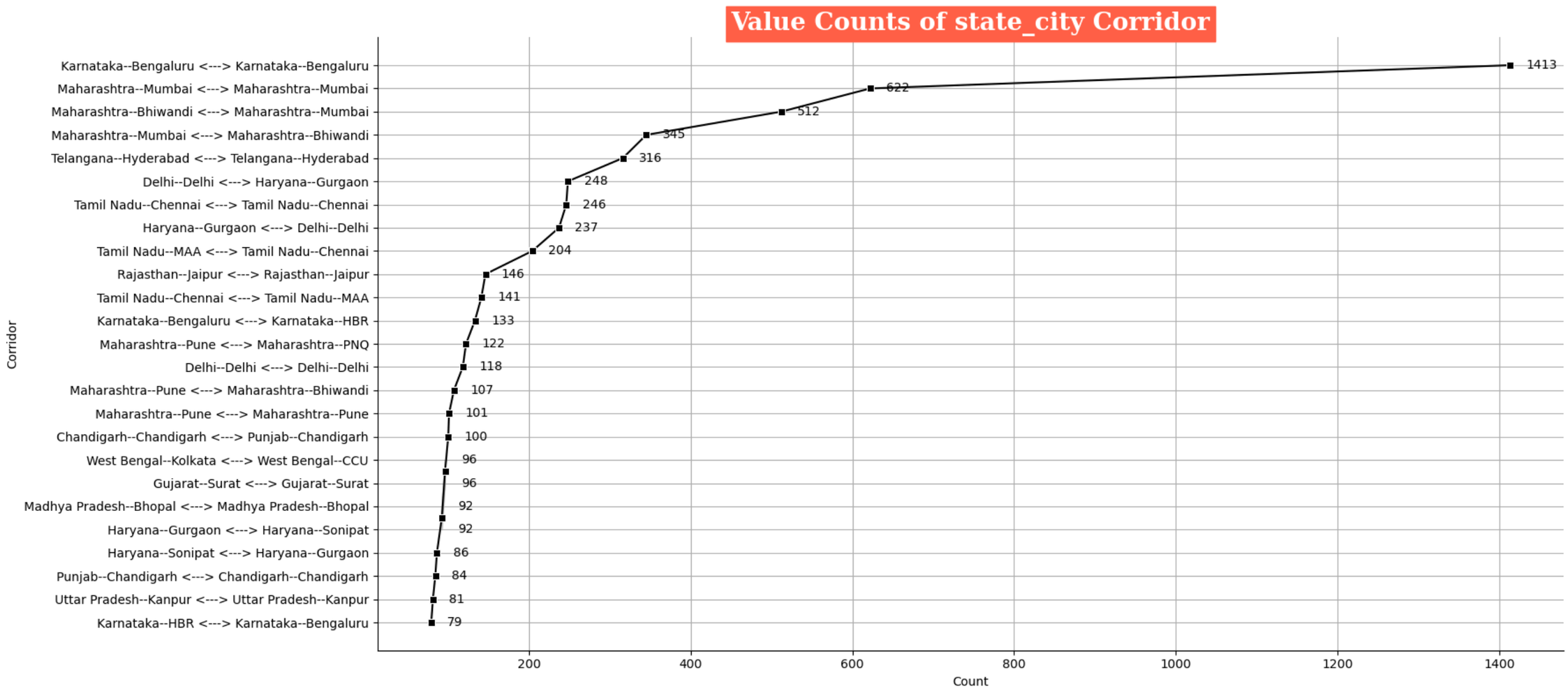
- The route between **Bangalore_Nelamangala_H** to **Bengaluru_KGAirport_HB**,**Bengaluru_Bomsndra_HB** sees the highest package volume, with 151 and 127 packages sent respectively.
- **Bengaluru_Bommasandra_HB** to **Bengaluru_KGAirport_HB** is also popular, with 121 packages sent.
- **Bengaluru_KGAirport_HB** 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.

In [92]:
```
de['state_corridor'] = de['source_state']+'--'+de['source_city'] +' <---> '+ de['destination_state']+'--'+de['destination_city']
de['state_corridor'].value_counts()
```

Out[92]:
```
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
```

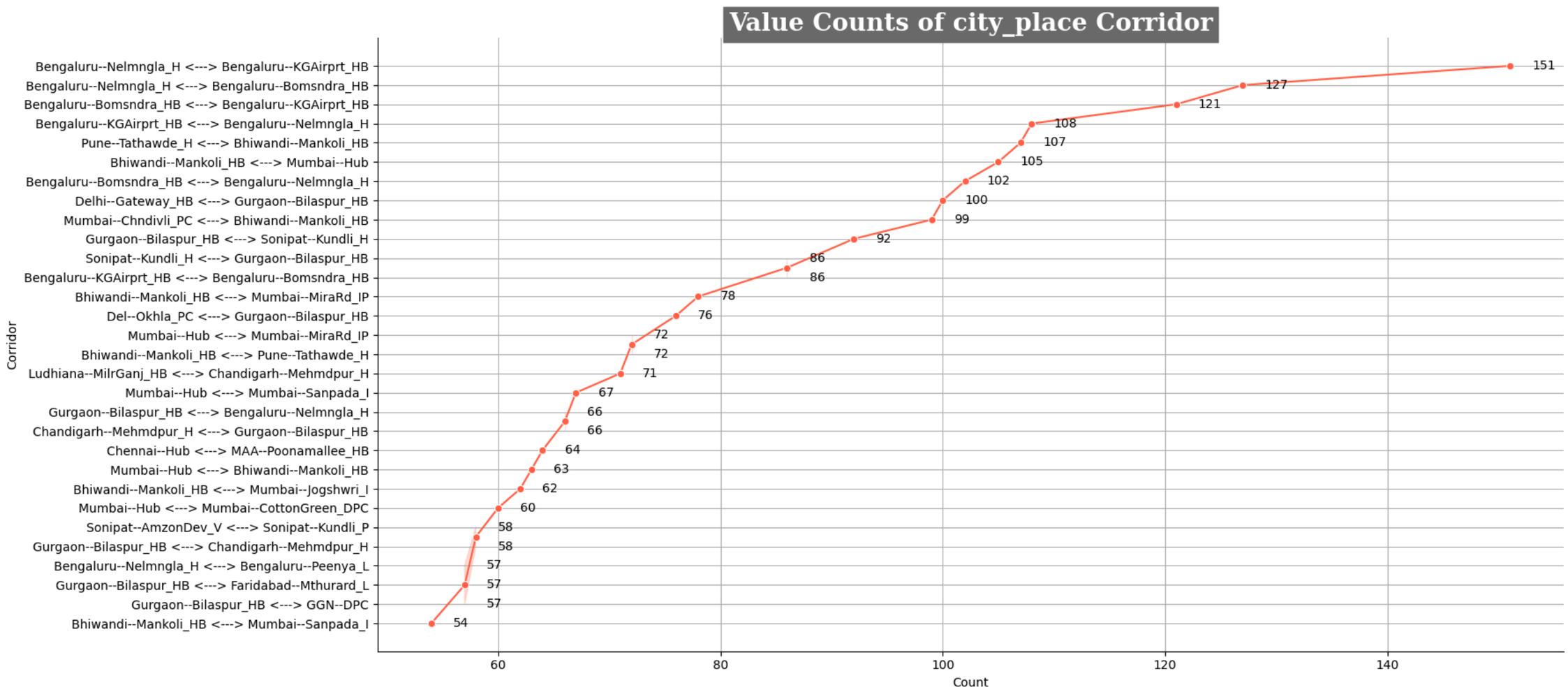
In [93]:
```
state_corridor_counts = de['state_corridor'].value_counts()[:25]

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()
```



In [94]:
```
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--KGAirprt_HB <---> Bengaluru--Nelmngla_H     108
Pune--Tathawde_H <---> Bhiwandi--Mankoli_HB            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
```

In [95]:
```
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.

In [97]:
```
# 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
```

Out[97]:

	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	actua
0	trip-153671041653548748+IND209304AAA+IND000000ACB	trip-153671041653548748	training	FTL	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_HB (Haryana)	2018-09-12 16:39:46.858469	2018-09-13 13:40:23.123744	1260.0	
1	trip-153671041653548748+IND462022AAA+IND209304AAA	trip-153671041653548748	training	FTL	2018-09-12 00:00:16.535741	Bhopal_Trnsport_H (Madhya Pradesh)	Kanpur_Central_H_6 (Uttar Pradesh)	2018-09-12 00:00:16.535741	2018-09-12 16:39:46.858469	999.0	
2	trip-153671042288605164+IND561203AAB+IND562101AAA	trip-153671042288605164	training	Carting	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSgr_D (Karnataka)	2018-09-12 02:03:09.655591	2018-09-12 03:01:59.598855	58.0	
3	trip-153671042288605164+IND572101AAA+IND561203AAB	trip-153671042288605164	training	Carting	2018-09-12 00:00:22.886430	Tumkur_Veersagr_I (Karnataka)	Doddablpur_ChikaDPP_D (Karnataka)	2018-09-12 00:00:22.886430	2018-09-12 02:03:09.655591	122.0	
4	trip-153671043369099517+IND000000ACB+IND160002AAC	trip-153671043369099517	training	FTL	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)	Chandigarh_Mehmdpur_H (Punjab)	2018-09-14 03:40:17.106733	2018-09-14 17:34:55.442454	834.0	
...	...	...	...	...	...	...	...	...	...	...	
26217	trip-153861115439069069+IND628204AAA+IND627657AAA	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	Tirchchndr_Shnmgprm_D (Tamil Nadu)	Thisayanvilai_UdnkdiRD_D (Tamil Nadu)	2018-10-04 02:29:04.272194	2018-10-04 03:31:11.183797	62.0	
26218	trip-153861115439069069+IND628613AAA+IND627005AAA	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	Peikulam_SriVnktpm_D (Tamil Nadu)	Tirunelveli_VdkkuSrt_I (Tamil Nadu)	2018-10-04 04:16:39.894872	2018-10-04 05:47:45.162682	91.0	
26219	trip-153861115439069069+IND628801AAA+IND628204AAA	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	Eral_Busstand_D (Tamil Nadu)	Tirchchndr_Shnmgprm_D (Tamil Nadu)	2018-10-04 01:44:53.808000	2018-10-04 02:29:04.272194	44.0	
26220	trip-153861118270144424+IND583119AAA+IND583101AAA	trip-153861118270144424	test	FTL	2018-10-03 23:59:42.701692	Sandur_WrdN1DPP_D (Karnataka)	Bellary_Dc (Karnataka)	2018-10-04 03:58:40.726547	2018-10-04 08:46:09.166940	287.0	
26221	trip-153861118270144424+IND583201AAA+IND583119AAA	trip-153861118270144424	test	FTL	2018-10-03 23:59:42.701692	Hospet (Karnataka)	Sandur_WrdN1DPP_D (Karnataka)	2018-10-04 02:51:44.712656	2018-10-04 03:58:40.726547	66.0	

26222 rows × 37 columns

🔷 In-Depth Analysis

In [98]:
```
new_df = de.copy()
```

In [99]:
```
new_df.columns
```

Out[99]:
```
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')
```

In [100…
```
new_df.sample(2)
```

Out[100]:

	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_dis
3330	trip-153694740553026744+IND574104AAA+IND574216AAA	trip-153694740553026744	training	Carting	2018-09-14 17:50:05.530477	Karkala_MarketRd_D (Karnataka)	Dhrmsthala_Beltngdi_D (Karnataka)	2018-09-15 02:48:16.030062	2018-09-15 04:38:56.729715	110.0	
3755	trip-153696604384005633+IND507117AAB+IND507303AAA	trip-153696604384005633	training	FTL	2018-09-14 23:00:43.840397	Manuguru_AskNagar_D (Telangana)	Sathupally_VidyaNGR_D (Telangana)	2018-09-15 04:15:30.426079	2018-09-15 07:28:59.609574	193.0	

In [101…
```
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
```

Out[101]:

	trip_uuid	data	route_type	od_start_time	od_end_time	od_time_diff_hour	trip_creation_time	trip_creation_month	trip_creation_year	trip_creation_day	trip_creation_hour	trip_creation_weekday	trip_creatic
0	trip-153671041653548748	training	FTL	2018-09-12 16:39:46.858469	2018-09-12 16:39:46.858469	37.668497	2018-09-12 00:00:16.535741	9	2018	12	0	2	
1	trip-153671042288605164	training	Carting	2018-09-12 02:03:09.655591	2018-09-12 02:03:09.655591	3.026865	2018-09-12 00:00:22.886430	9	2018	12	0	2	
2	trip-153671043369099517	training	FTL	2018-09-14 03:40:17.106733	2018-09-14 03:40:17.106733	65.572709	2018-09-12 00:00:33.691250	9	2018	12	0	2	
3	trip-153671046011330457	training	Carting	2018-09-12 00:01:00.113710	2018-09-12 01:41:29.809822	1.674916	2018-09-12 00:01:00.113710	9	2018	12	0	2	
4	trip-153671052974046625	training	FTL	2018-09-12 00:02:09.740725	2018-09-12 03:54:43.114421	11.972484	2018-09-12 00:02:09.740725	9	2018	12	0	2	
...	...	...	...	...	...	...	...	...	...	...	...	...	...
14782	trip-153861095625827784	test	Carting	2018-10-03 23:55:56.258533	2018-10-04 06:41:25.409035	4.300482	2018-10-03 23:55:56.258533	10	2018	3	23	2	
14783	trip-153861104386292051	test	Carting	2018-10-03 23:57:23.863155	2018-10-04 00:57:59.294434	1.009842	2018-10-03 23:57:23.863155	10	2018	3	23	2	
14784	trip-153861106442901555	test	Carting	2018-10-04 02:51:27.075797	2018-10-04 02:51:27.075797	7.035331	2018-10-03 23:57:44.429324	10	2018	3	23	2	
14785	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	2018-10-04 02:29:04.272194	5.808548	2018-10-03 23:59:14.390954	10	2018	3	23	2	
14786	trip-153861118270144424	test	FTL	2018-10-04 03:58:40.726547	2018-10-04 03:58:40.726547	5.906793	2018-10-03 23:59:42.701692	10	2018	3	23	2	

14787 rows × 35 columns

In [102…

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

Out[102]:

	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_tin
0	37.668497	2259.0	824.732849	1562.0	717.0	991.352295	1548.0	1008.0	1320.473267	1548.0	
1	3.026865	180.0	73.186905	143.0	68.0	85.111000	141.0	65.0	84.189400	141.0	
2	65.572709	3933.0	1927.404297	3347.0	1740.0	2354.066650	3308.0	1941.0	2545.267822	3308.0	
3	1.674916	100.0	17.175274	59.0	15.0	19.680000	59.0	16.0	19.876600	59.0	
4	11.972484	717.0	127.448502	341.0	117.0	146.791794	340.0	115.0	146.791901	340.0	
...	...	...	...	...	...	...	...	...	...	...	
14782	4.300482	257.0	57.762333	83.0	62.0	73.462997	82.0	62.0	64.855103	82.0	
14783	1.009842	60.0	15.513784	21.0	12.0	16.088200	21.0	11.0	16.088299	21.0	
14784	7.035331	421.0	38.684837	282.0	48.0	58.903702	281.0	88.0	104.886597	281.0	
14785	5.808548	347.0	134.723831	264.0	179.0	171.110306	258.0	221.0	223.532394	258.0	
14786	5.906793	353.0	66.081528	275.0	68.0	80.578705	274.0	67.0	80.578705	274.0	

14787 rows × 12 columns

In [103…

```
numerical_columns.describe().T
```

Out[103]:

	count	mean	std	min	25%	50%	75%	max
od_time_diff_hour	14787.0	8.840187	10.978880	0.391024	2.494975	4.661846	10.558962	131.642533
start_scan_to_end_scan	14787.0	529.429016	658.254395	23.000000	149.000000	279.000000	632.000000	7898.000000
actual_distance_to_destination	14787.0	164.090195	305.502808	9.002461	22.777099	48.287895	163.591255	2186.531738
actual_time	14787.0	356.306000	561.517761	9.000000	67.000000	148.000000	367.000000	6265.000000
osrm_time	14787.0	160.990936	271.459229	6.000000	29.000000	60.000000	168.000000	2032.000000
osrm_distance	14787.0	203.887405	370.565460	9.072900	30.756900	65.302795	206.644203	2840.081055
segment_actual_time	14787.0	353.059174	556.364441	9.000000	66.000000	147.000000	364.000000	6230.000000
segment_osrm_time	14787.0	180.511597	314.678741	6.000000	30.000000	65.000000	184.000000	2564.000000
segment_osrm_distance	14787.0	222.705444	416.845642	9.072900	32.578850	69.784203	216.560608	3523.632324
segment_actual_time_sum	14787.0	353.059174	556.364441	9.000000	66.000000	147.000000	364.000000	6230.000000
segment_osrm_time_sum	14787.0	180.511597	314.678741	6.000000	30.000000	65.000000	184.000000	2564.000000
segment_osrm_distance_sum	14787.0	222.705444	416.845642	9.072900	32.578850	69.784203	216.560608	3523.632324

In [104…

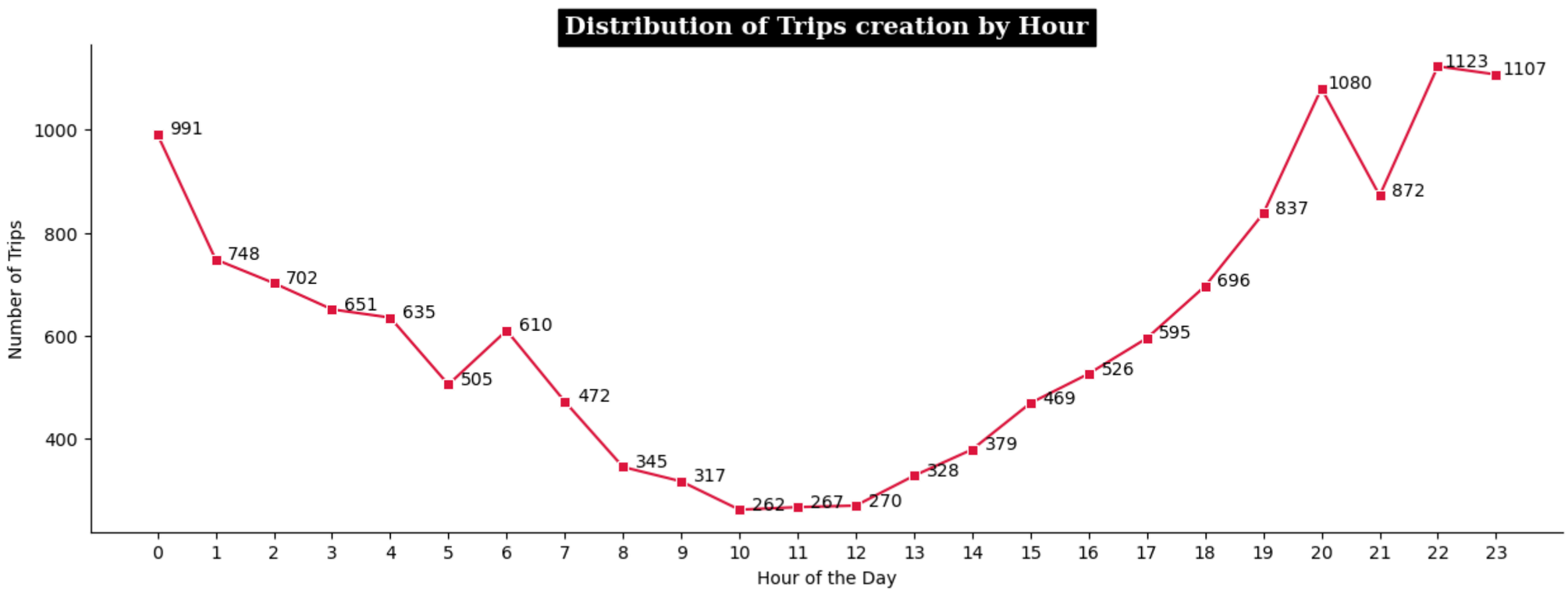
```
trip_agg_df.describe(include = object).T
```

Out[104]:

	count	unique	top	freq
trip_uuid	14787	14787	trip-153671041653548748	1
source_name	14787	930	Gurgaon_Bilaspur_HB (Haryana)	1052
source_city	14787	713	Bengaluru	1700
source_state	14787	29	Maharashtra	2714
source_place	14787	788	Bilaspur_HB	1052
destination_name	14787	1042	Gurgaon_Bilaspur_HB (Haryana)	745
destination_city	14787	851	Bengaluru	1633
destination_state	14787	32	Maharashtra	2569
destination_place	14787	866	Bilaspur_HB	745
corridor	14787	1737	Bangalore_Nelmngla_H (Karnataka) <---> Bengalu...	151
state_corridor	14787	1366	Karnataka--Bengaluru <---> Karnataka--Bengaluru	1333
city_corridor	14787	1737	Bengaluru--Nelmngla_H <---> Bengaluru--KGAirpr...	151

In [105…
```
trip_df = trip_agg_df.copy()
```

In [106…
```
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()
```



In [107…
```
trip_df.sample()
```

Out[107]:

	trip_uuid	data	route_type	od_start_time	od_end_time	od_time_diff_hour	trip_creation_time	trip_creation_month	trip_creation_year	trip_creation_day	trip_creation_hour	trip_creation_weekday	trip_creatior
7917	trip-153765583943264913	training	Carting	2018-09-22 22:37:19.432896	2018-09-22 23:19:42.965506	0.706537	2018-09-22 22:37:19.432896	9	2018	22	22	5	

In [108…
```
trip_df.trip_creation_year.value_counts()
```

Out[108]:
```
trip_creation_year
2018    14787
Name: count, dtype: int64
```

In [109…
```
trip_df.trip_creation_month.value_counts()
```

Out[109]:
```
trip_creation_month
9     13011
10     1776
Name: count, dtype: int64
```

In [110…
```
trip_df['trip_creation_month'].value_counts(normalize = True) * 100
```

Out[110]:
```
trip_creation_month
9     87.98945
10    12.01055
Name: proportion, dtype: float64
```

In [111…
```
trip_df.trip_creation_week.value_counts()
```

Out[111]:
```
trip_creation_week
38    5001
39    4402
37    3608
40    1776
Name: count, dtype: Int64
```

In [112…
```
trip_df.trip_creation_weekday.value_counts(ascending=True)
```

Out[112]:
```
trip_creation_weekday
6    1753
0    1980
1    2035
4    2057
3    2103
5    2128
2    2731
Name: count, dtype: int64
```

In [113…
```
trip_df['trip_creation_day_week'] = trip_df['trip_creation_time'].dt.day_name()
```

In [114…
```
trip_df.trip_creation_day.value_counts()
```

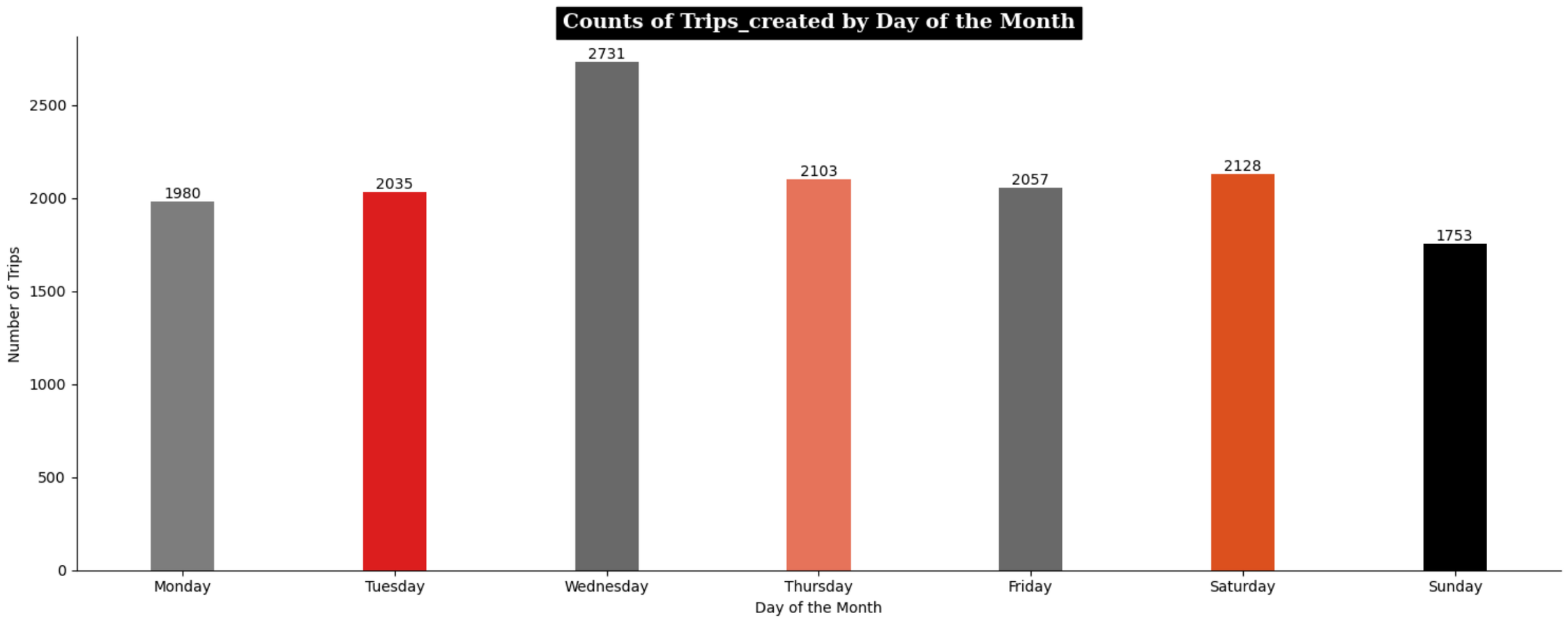
Out[114]:
```
trip_creation_day
18    791
15    783
13    750
12    747
21    740
22    740
17    722
14    712
20    703
25    695
26    683
19    674
24    658
27    650
23    631
3     627
16    616
28    605
29    605
1     600
2     549
30    506
Name: count, dtype: int64
```

In [123…
```
trip_df.sample()
```

Out[123]:

	trip_uuid	data	route_type	od_start_time	od_end_time	od_time_diff_hour	trip_creation_time	trip_creation_month	trip_creation_year	trip_creation_day	trip_creation_hour	trip_creation_weekday	trip_creatior
8403	trip-153772987770593762	training	FTL	2018-09-24 00:14:22.226774	2018-09-24 02:42:00.976996	3.847563	2018-09-23 19:11:17.706293	9	2018	23	19	6	

In [125…
```
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()
```



In [126…
```
trip_df['trip_creation_dayofdate'] = trip_df['trip_creation_time'].dt.day
```

In [127…
```
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

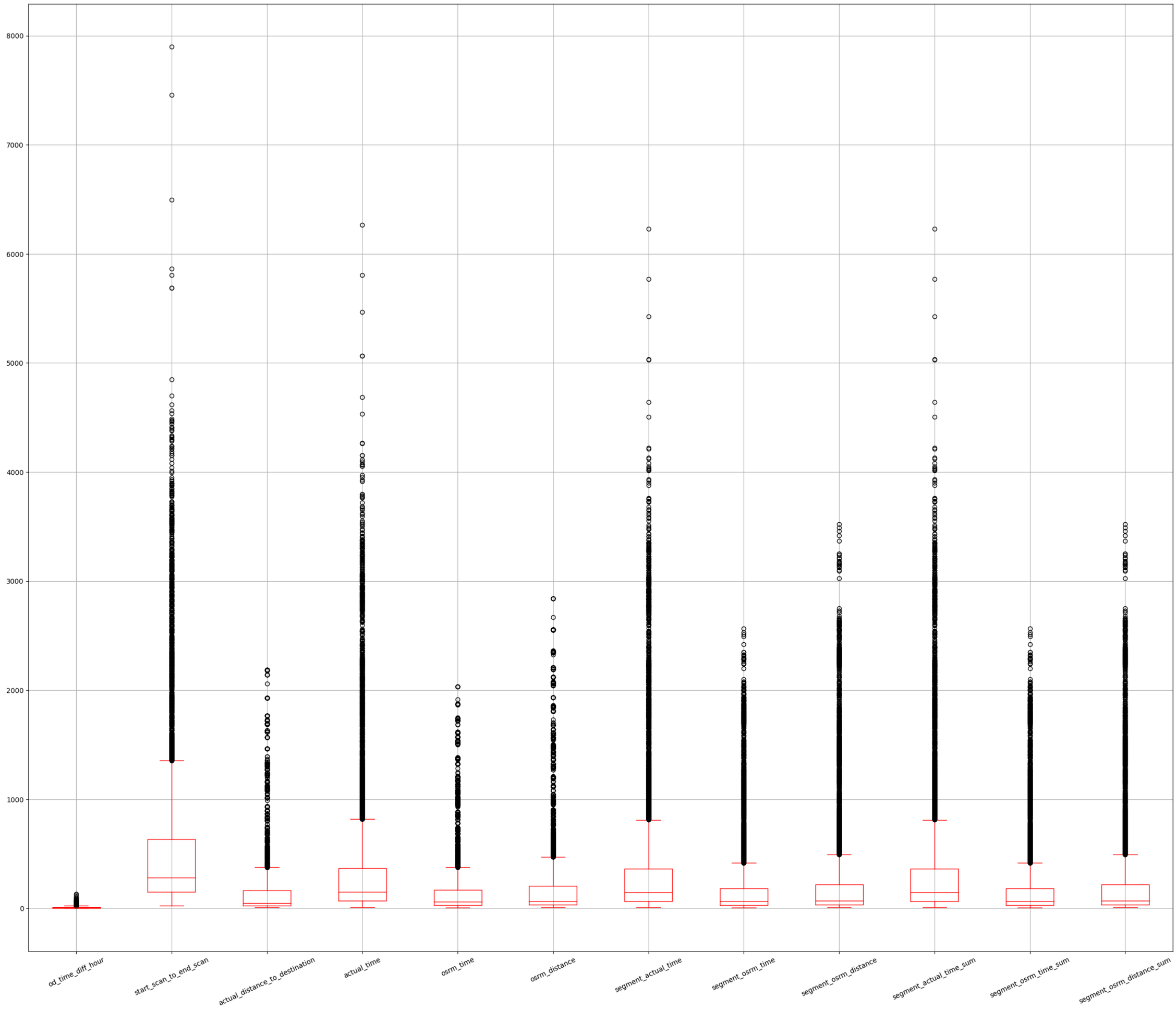
In [128…
```
numerical_columns
```

Out[128]:

	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_tin
0	37.668497	2259.0	824.732849	1562.0	717.0	991.352295	1548.0	1008.0	1320.473267	1548.0	
1	3.026865	180.0	73.186905	143.0	68.0	85.111000	141.0	65.0	84.189400	141.0	
2	65.572709	3933.0	1927.404297	3347.0	1740.0	2354.066650	3308.0	1941.0	2545.267822	3308.0	
3	1.674916	100.0	17.175274	59.0	15.0	19.680000	59.0	16.0	19.876600	59.0	
4	11.972484	717.0	127.448502	341.0	117.0	146.791794	340.0	115.0	146.791901	340.0	
...	...	...	...	...	...	...	...	...	...	...	
14782	4.300482	257.0	57.762333	83.0	62.0	73.462997	82.0	62.0	64.855103	82.0	
14783	1.009842	60.0	15.513784	21.0	12.0	16.088200	21.0	11.0	16.088299	21.0	
14784	7.035331	421.0	38.684837	282.0	48.0	58.903702	281.0	88.0	104.886597	281.0	
14785	5.808548	347.0	134.723831	264.0	179.0	171.110306	258.0	221.0	223.532394	258.0	
14786	5.906793	353.0	66.081528	275.0	68.0	80.578705	274.0	67.0	80.578705	274.0	

14787 rows × 12 columns

In [129…
```
plt.figure(figsize=(30, 25))
numerical_columns.boxplot(rot=25, figsize=(35,20), color = 'r')
plt.grid('off')
plt.show()
```



In [130…
```
numerical_columns.columns
```

Out[130]:
```
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')
```

In [131…
```
num_cols = numerical_columns.columns.tolist()
num_cols
```

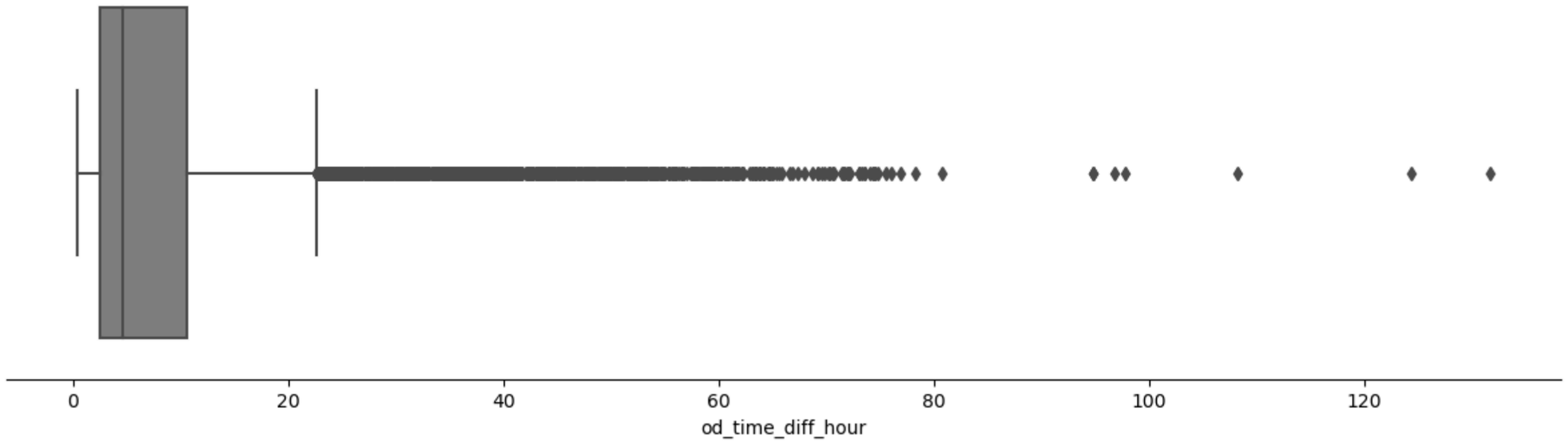
Out[131]:
```
['od_time_diff_hour',
 'start_scan_to_end_scan',
 'actual_distance_to_destination',
 'actual_time',
 'osrm_time',
 'osrm_distance',
 'segment_actual_time',
 'segment_osrm_time',
 'segment_osrm_distance',
 'segment_actual_time_sum',
 'segment_osrm_time_sum',
 'segment_osrm_distance_sum']
```

In [132…
```
# 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)
```

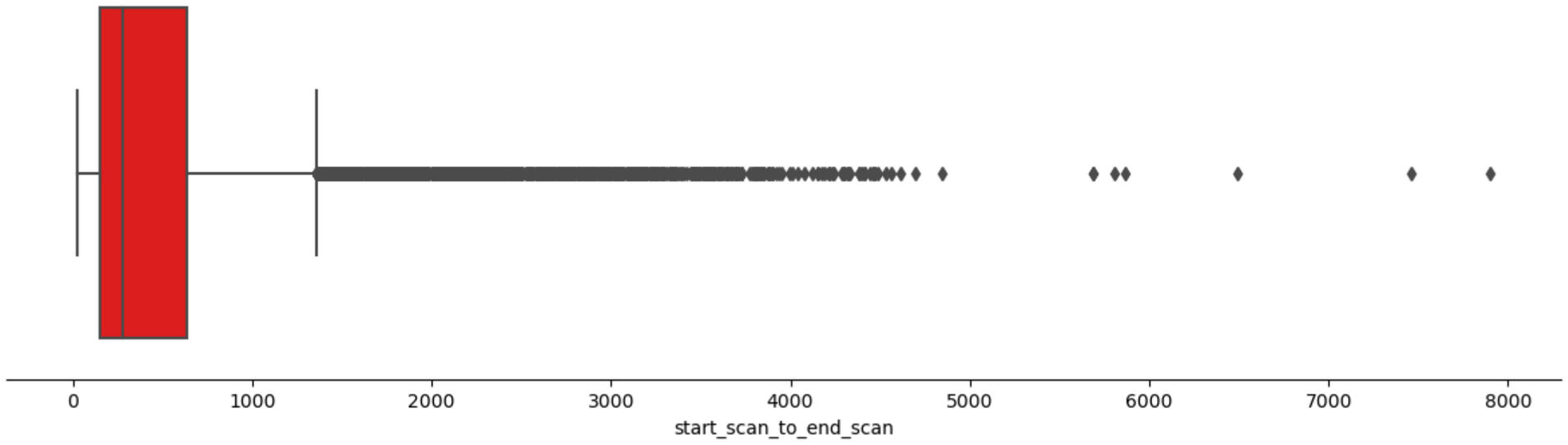
```
od_time_diff_hour                  8.063987
start_scan_to_end_scan           483.000000
actual_distance_to_destination   140.814157
actual_time                      300.000000
osrm_time                        139.000000
osrm_distance                    175.887303
segment_actual_time              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
```

In [133…
```
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()
```

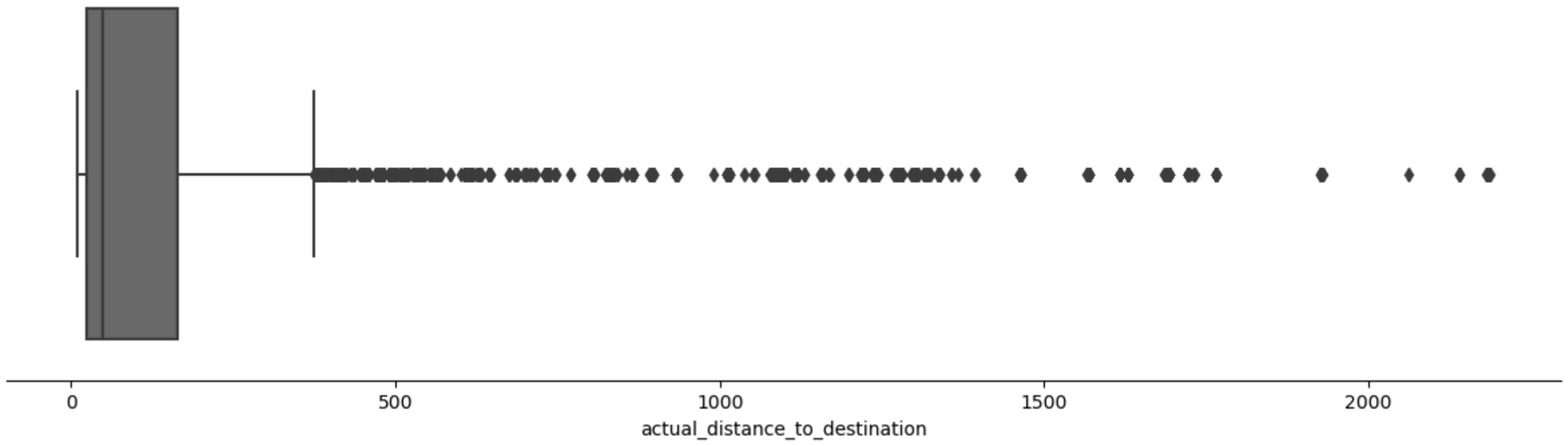
Boxplot of od_time_diff_hour



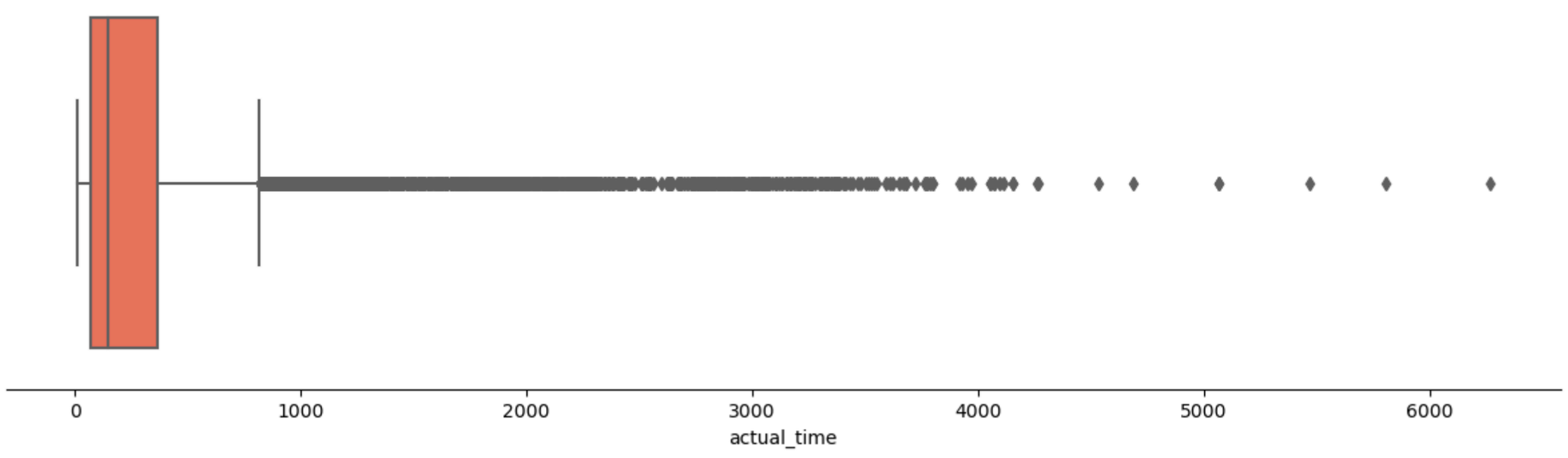
Boxplot of start_scan_to_end_scan



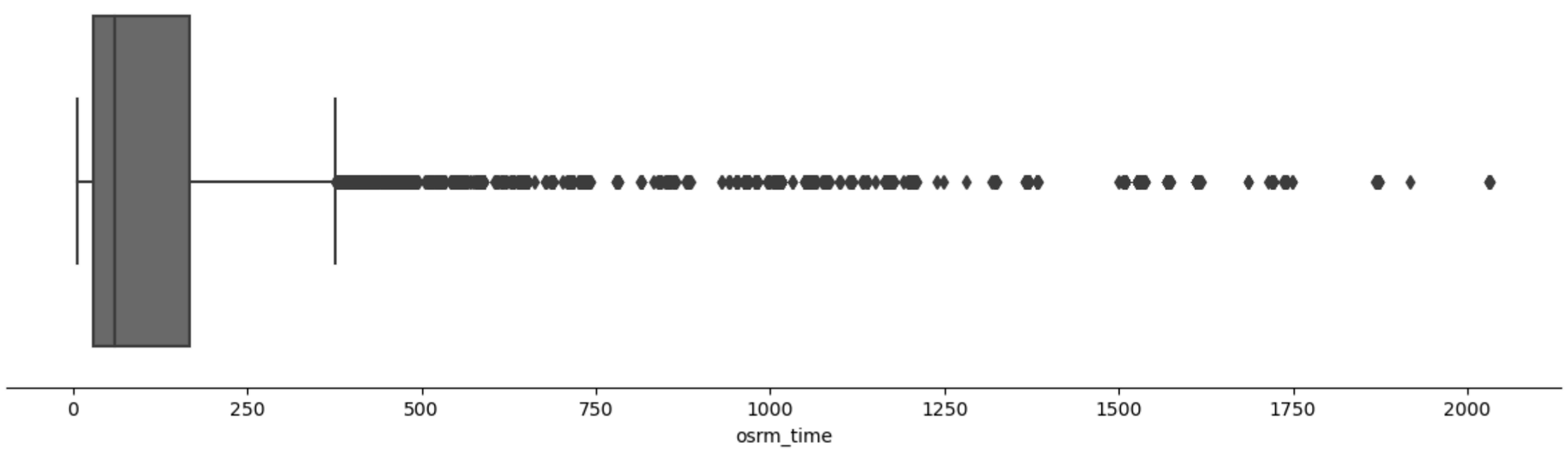
Boxplot of actual_distance_to_destination



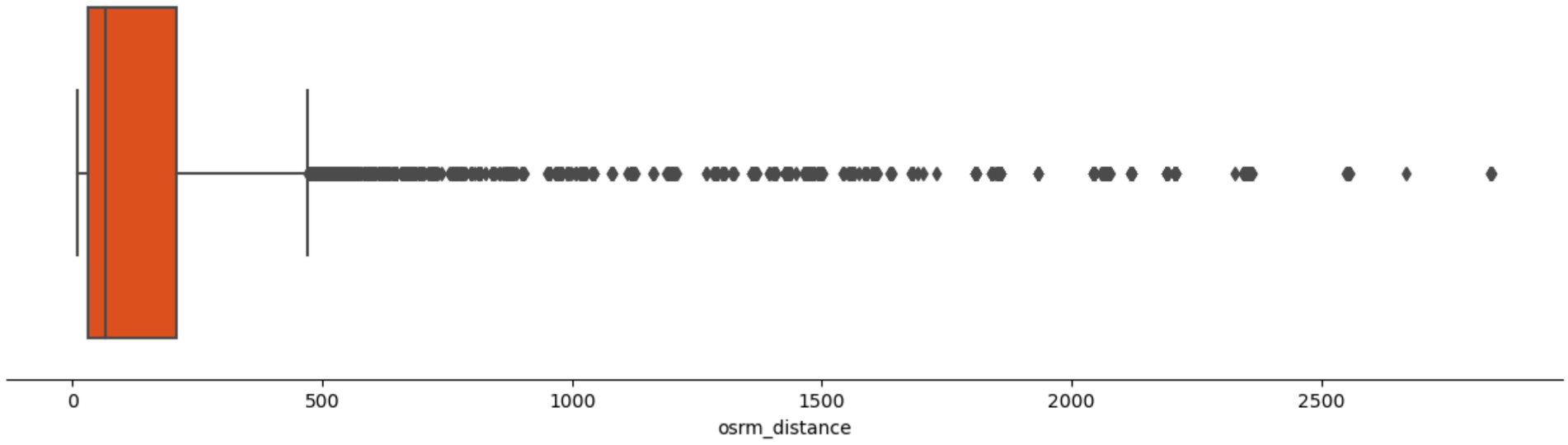
Boxplot of actual_time



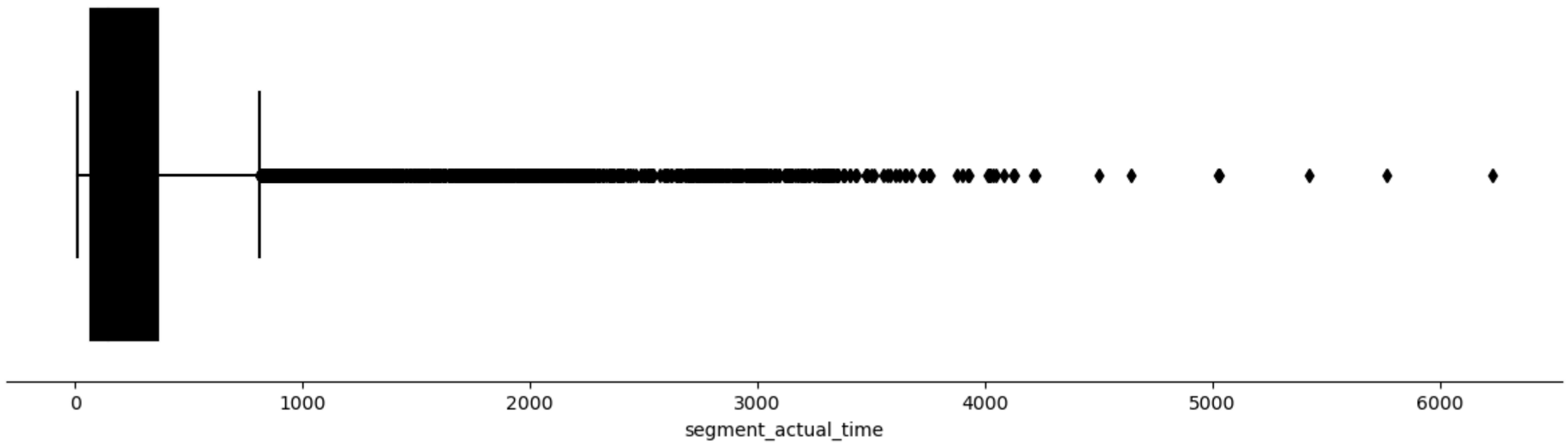
Boxplot of osrm_time



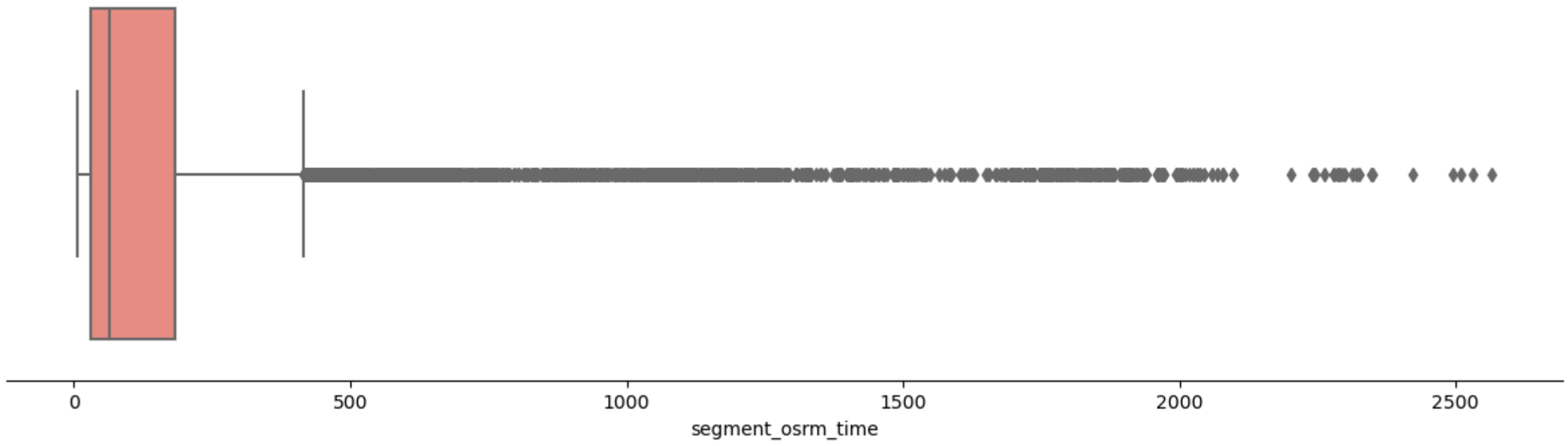
Boxplot of osrm_distance



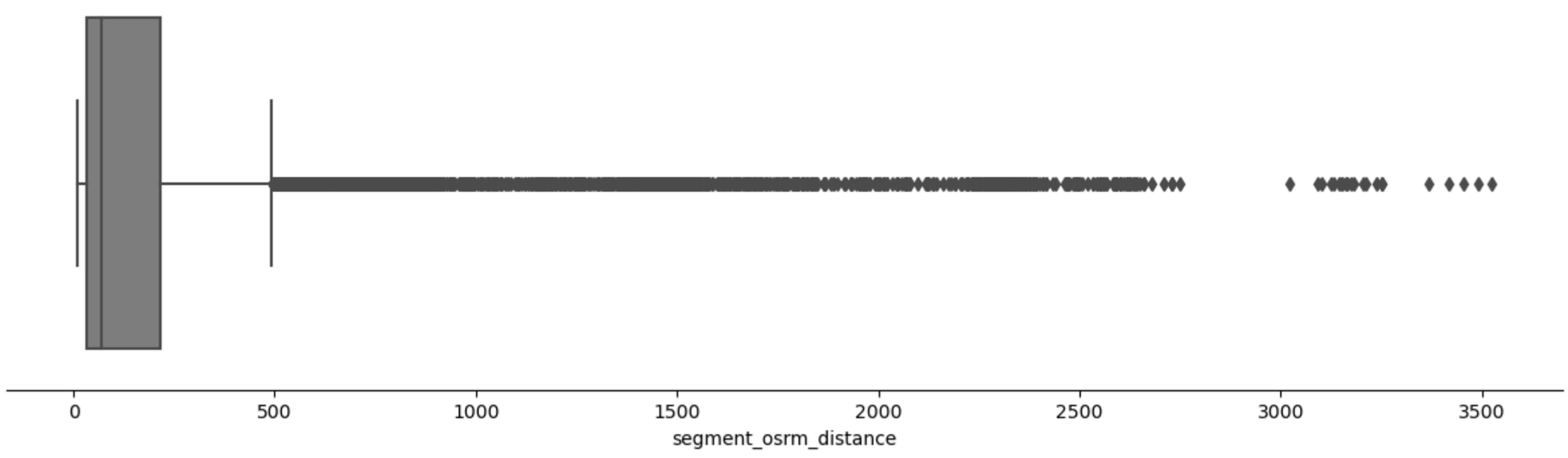
Boxplot of segment_actual_time



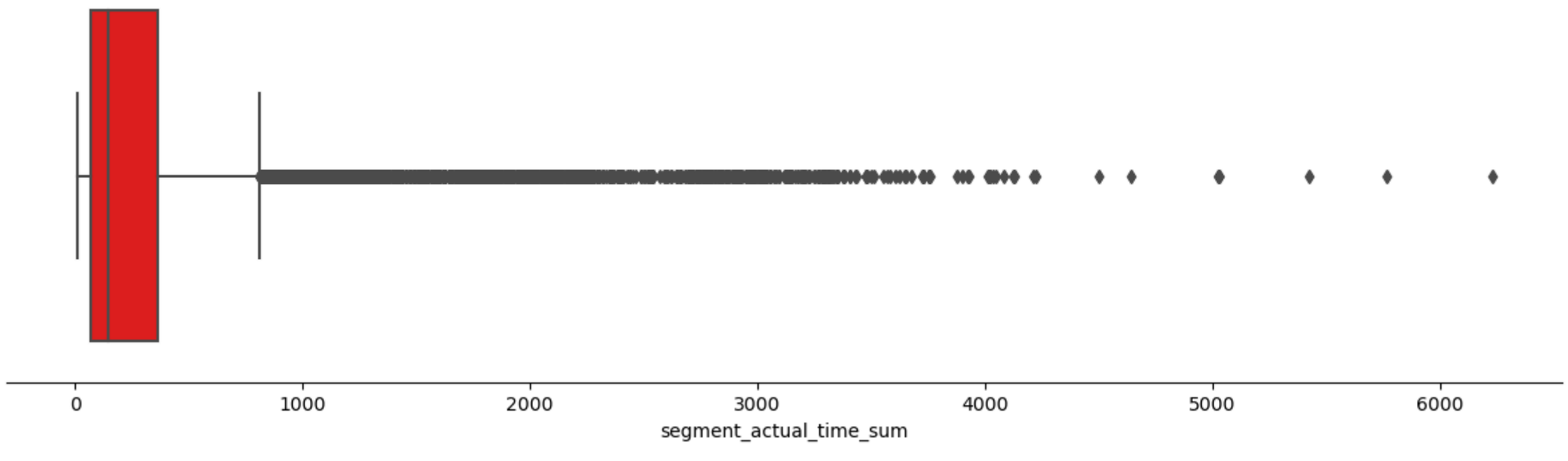
Boxplot of segment_osrm_time

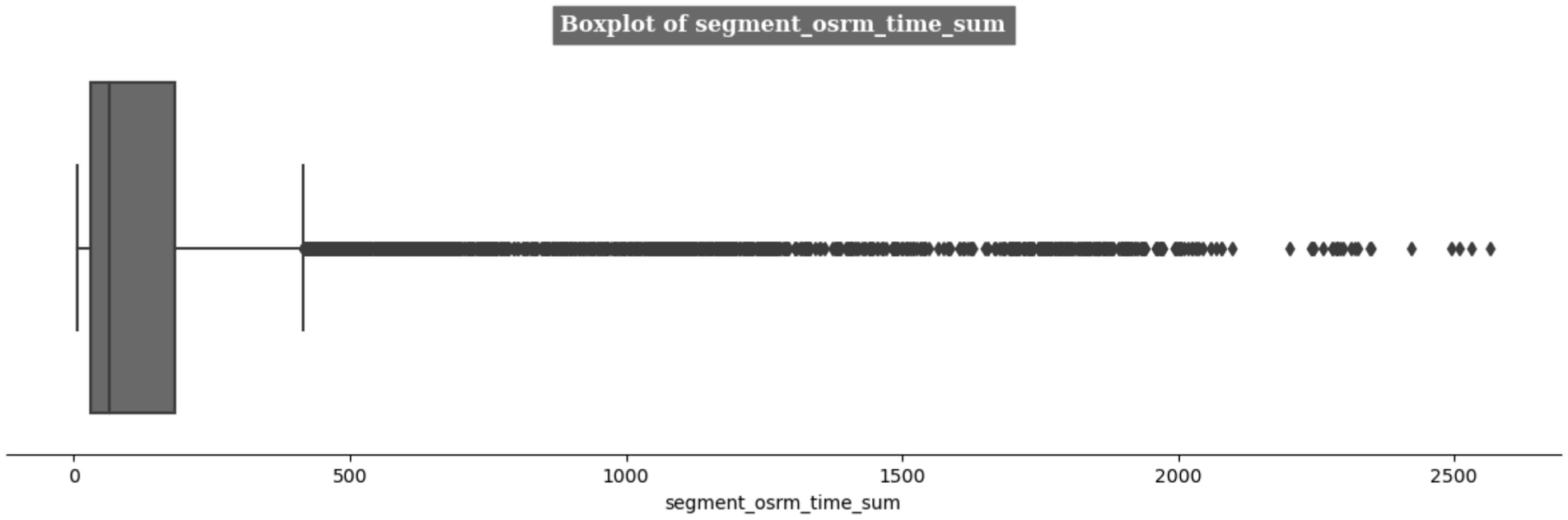


Boxplot of segment_osrm_distance



Boxplot of segment_actual_time_sum





Outlier Removal

In [134…

```
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 × 1 columns

```
Clipped data of od_time_diff_hour
```

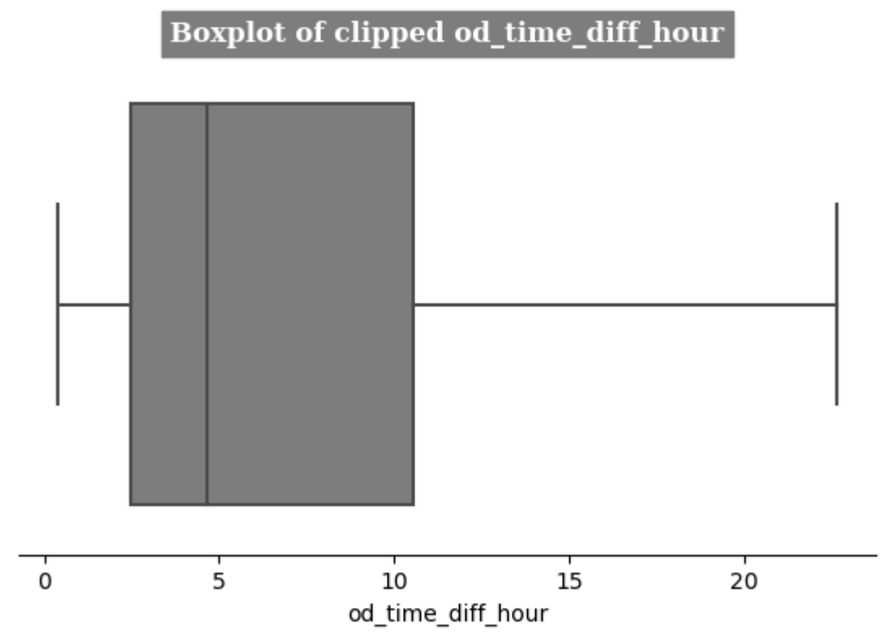
	od_time_diff_hour
0	22.654942
1	3.026865
2	22.654942
3	1.674916
4	11.972484
...	...
14782	4.300482
14783	1.009842
14784	7.035331
14785	5.808548
14786	5.906793

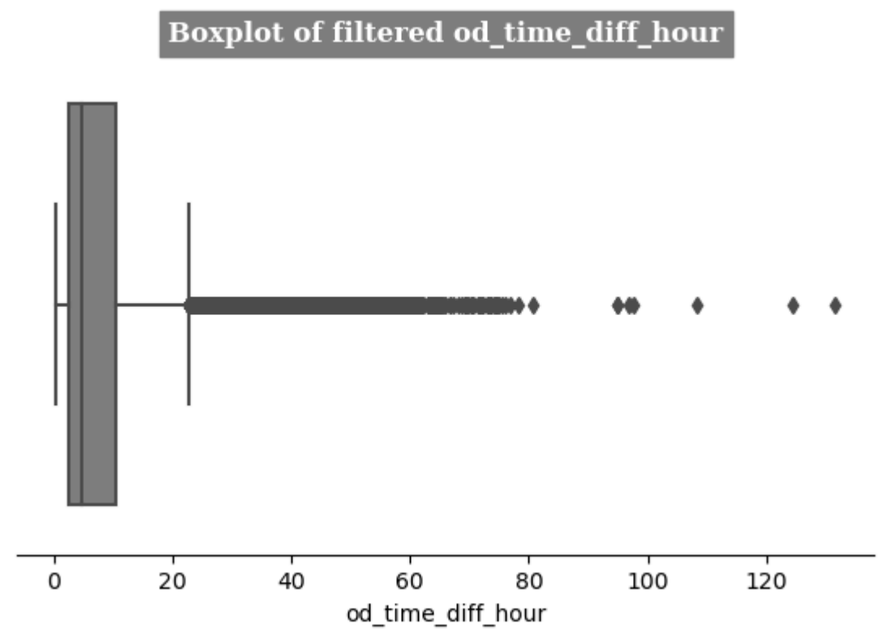
14787 rows × 1 columns

```
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 × 1 columns





	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 × 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

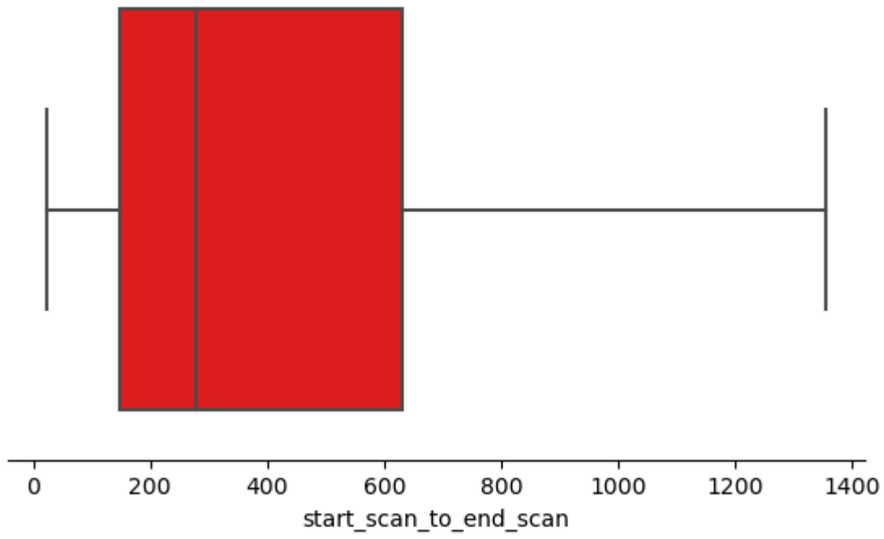
14787 rows × 1 columns

```
Filtered data of start_scan_to_end_scan
```

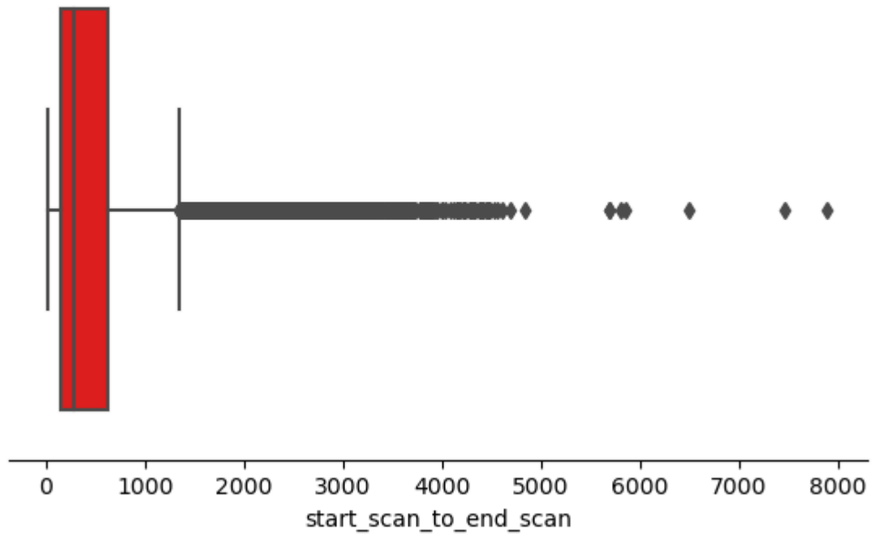
	start_scan_to_end_scan
0	2259.0
1	180.0
2	3933.0
3	100.0
4	717.0
...	...
14782	257.0
14783	60.0
14784	421.0
14785	347.0
14786	353.0

14787 rows × 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	57.762333
14783	15.513784
14784	38.684837
14785	134.723831
14786	66.081528

14787 rows × 1 columns

`Clipped data of actual_distance_to_destination`

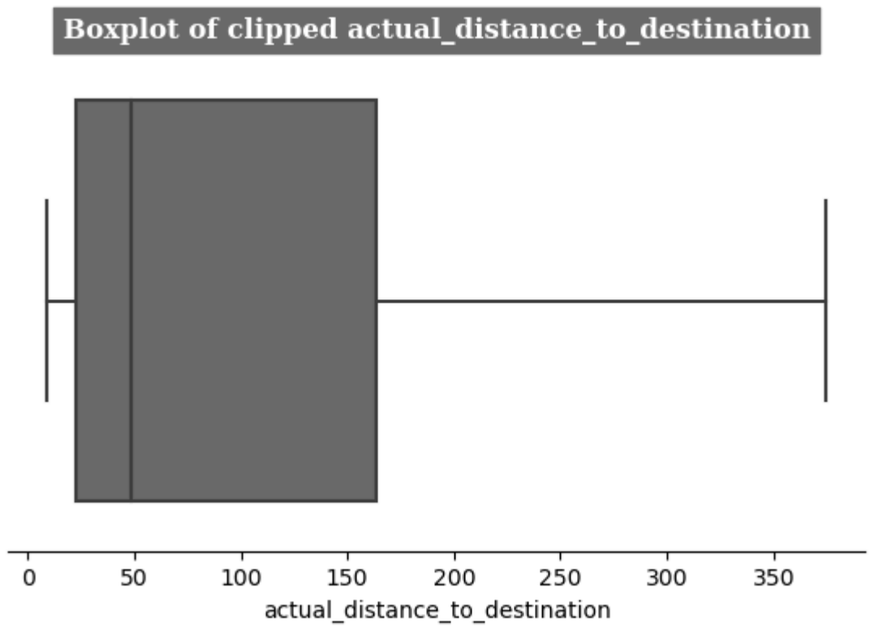
	actual_distance_to_destination
0	374.812490
1	73.186905
2	374.812490
3	17.175274
4	127.448502
...	...
14782	57.762333
14783	15.513784
14784	38.684837
14785	134.723831
14786	66.081528

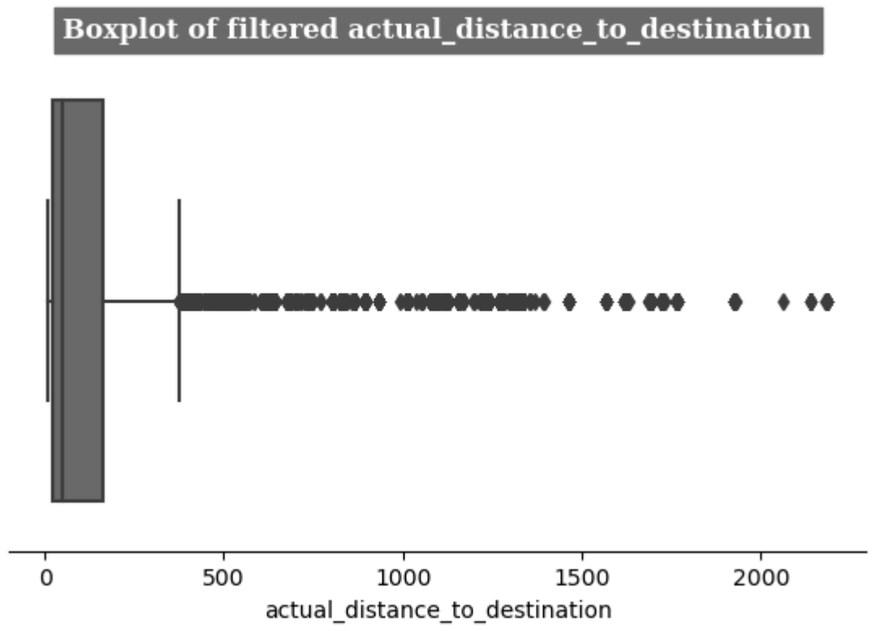
14787 rows × 1 columns

`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	57.762333
14783	15.513784
14784	38.684837
14785	134.723831
14786	66.081528

14787 rows × 1 columns





	actual_time
0	1562.0
1	143.0
2	3347.0
3	59.0
4	341.0
...	...
14782	83.0
14783	21.0
14784	282.0
14785	264.0
14786	275.0

14787 rows × 1 columns

```
Clipped data of actual_time
```

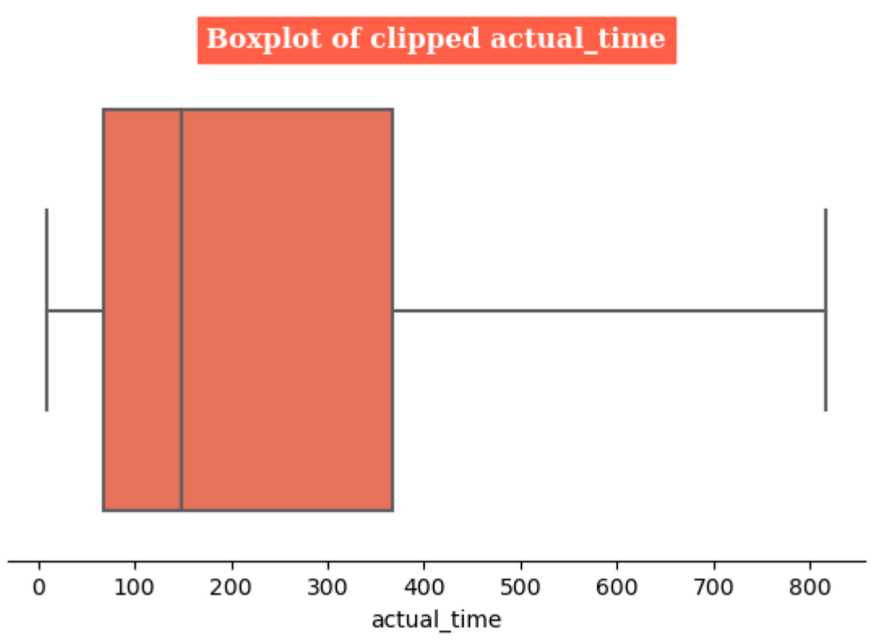
	actual_time
0	817.0
1	143.0
2	817.0
3	59.0
4	341.0
...	...
14782	83.0
14783	21.0
14784	282.0
14785	264.0
14786	275.0

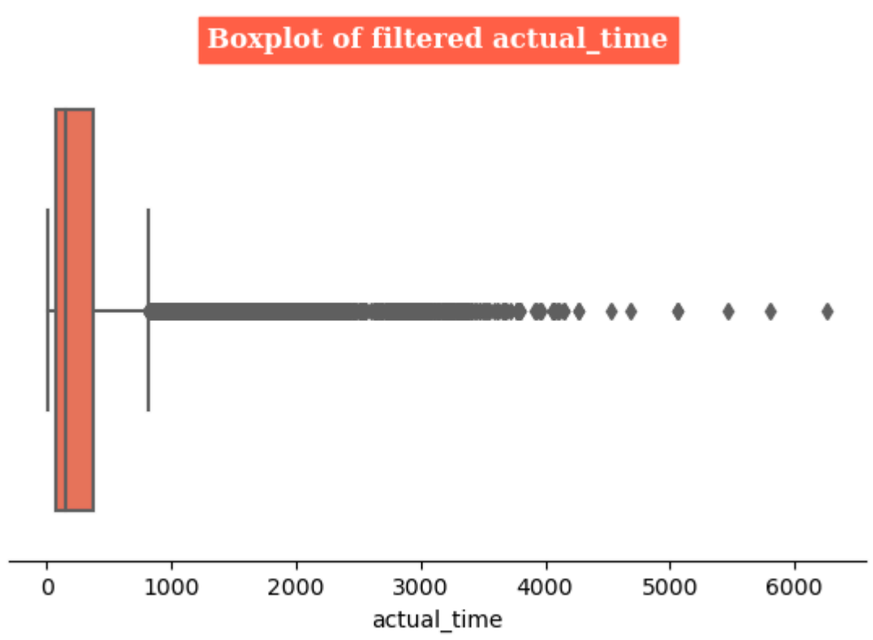
14787 rows × 1 columns

```
Filtered data of actual_time
```

	actual_time
0	1562.0
1	143.0
2	3347.0
3	59.0
4	341.0
...	...
14782	83.0
14783	21.0
14784	282.0
14785	264.0
14786	275.0

14787 rows × 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 × 1 columns

```
Clipped data of osrm_time
```

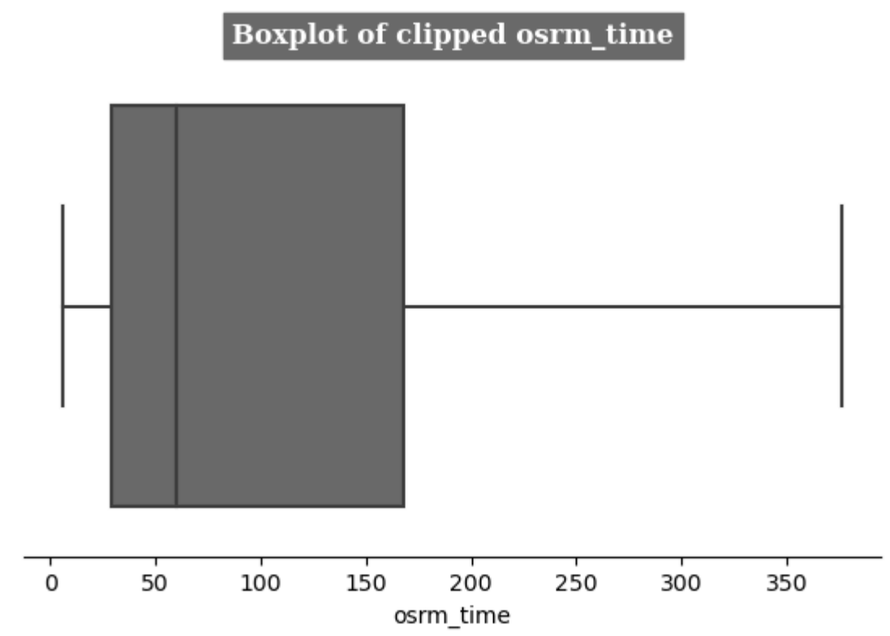
	osrm_time
0	376.5
1	68.0
2	376.5
3	15.0
4	117.0
...	...
14782	62.0
14783	12.0
14784	48.0
14785	179.0
14786	68.0

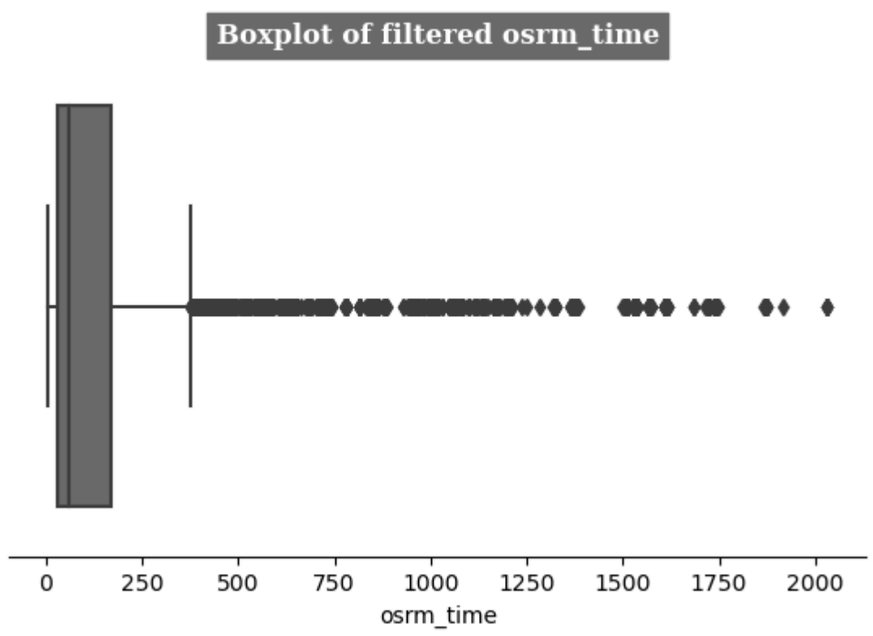
14787 rows × 1 columns

```
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 × 1 columns





	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 × 1 columns

```
Clipped data of osrm_distance
```

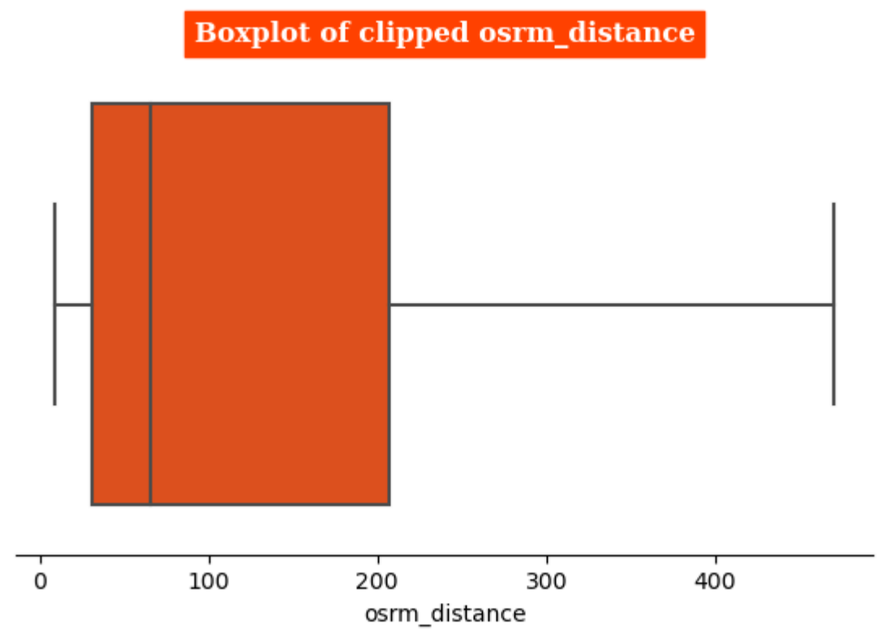
	osrm_distance
0	470.475158
1	85.111000
2	470.475158
3	19.680000
4	146.791794
...	...
14782	73.462997
14783	16.088200
14784	58.903702
14785	171.110306
14786	80.578705

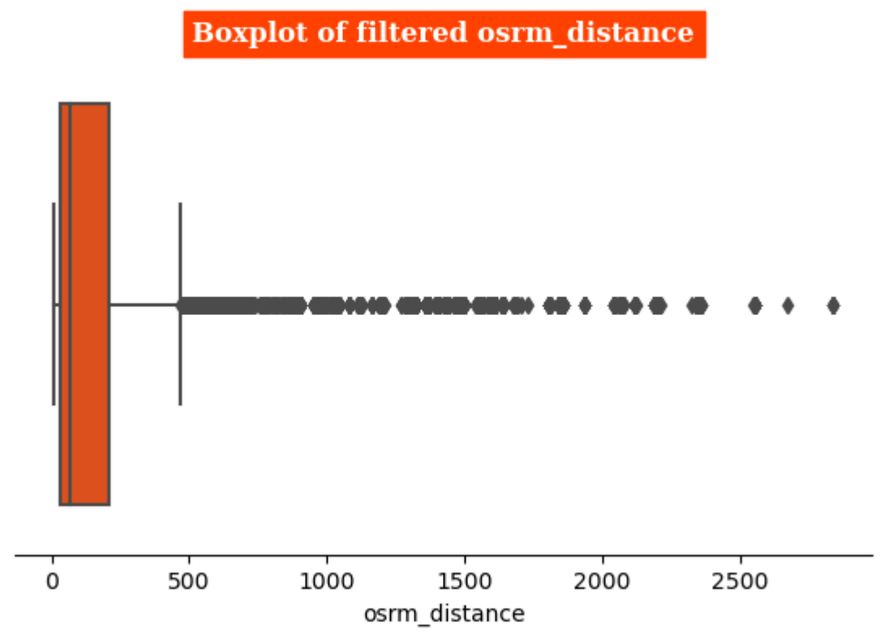
14787 rows × 1 columns

```
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 × 1 columns





	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 × 1 columns

```
Clipped data of segment_actual_time
```

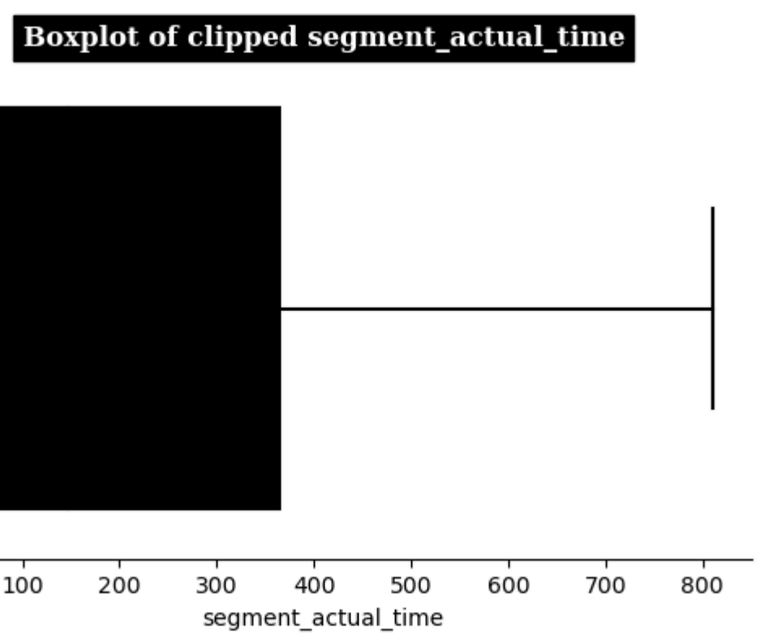
	segment_actual_time
0	811.0
1	141.0
2	811.0
3	59.0
4	340.0
...	...
14782	82.0
14783	21.0
14784	281.0
14785	258.0
14786	274.0

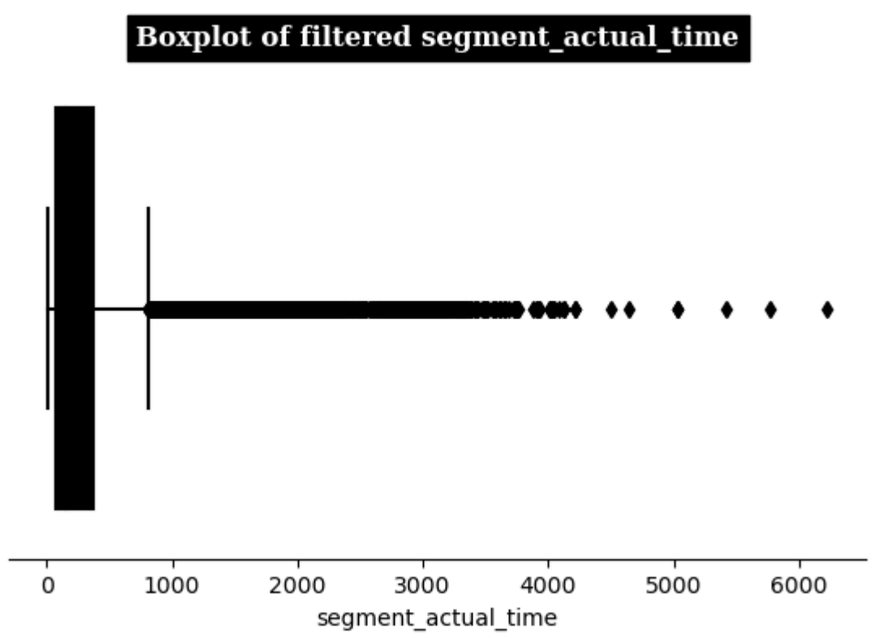
14787 rows × 1 columns

```
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	82.0
14783	21.0
14784	281.0
14785	258.0
14786	274.0

14787 rows × 1 columns





	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 × 1 columns

Clipped data of segment_osrm_time

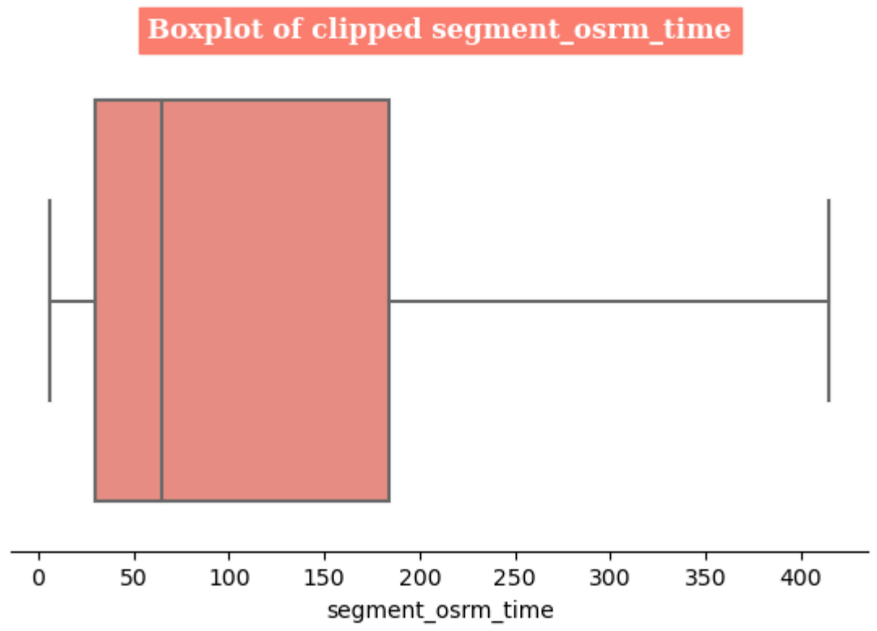
	segment_osrm_time
0	415.0
1	65.0
2	415.0
3	16.0
4	115.0
...	...
14782	62.0
14783	11.0
14784	88.0
14785	221.0
14786	67.0

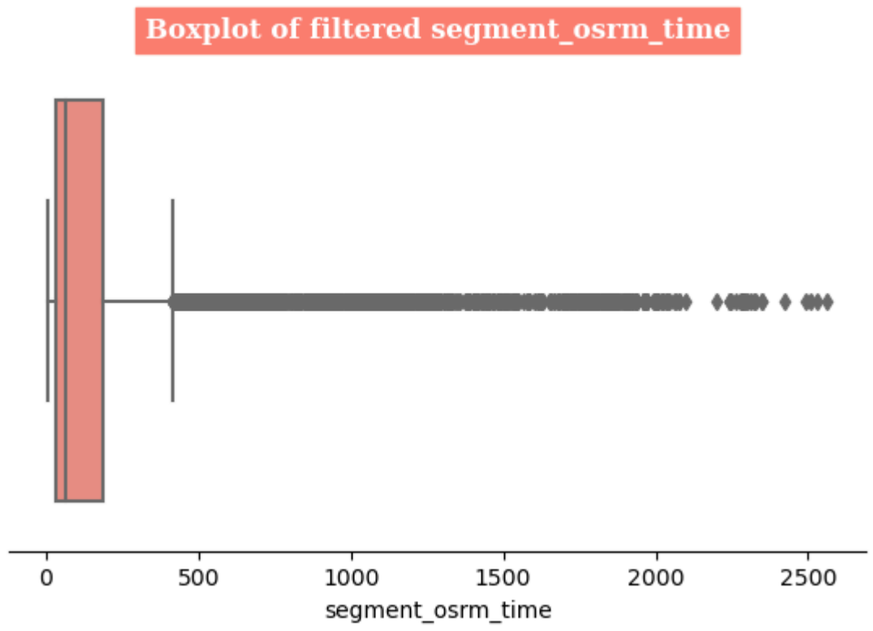
14787 rows × 1 columns

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 × 1 columns





	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 × 1 columns

`Clipped data of segment_osrm_distance`

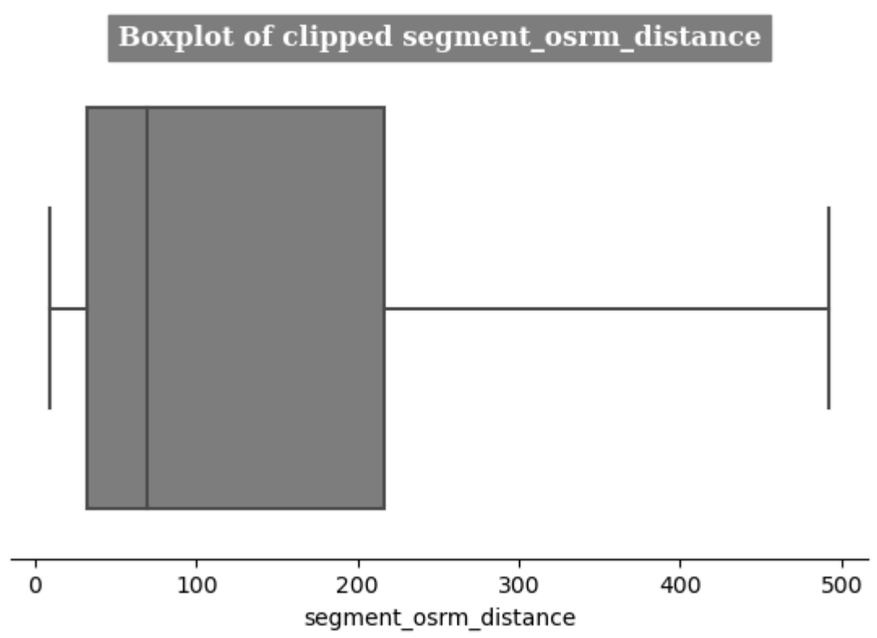
	segment_osrm_distance
0	492.533245
1	84.189400
2	492.533245
3	19.876600
4	146.791901
...	...
14782	64.855103
14783	16.088299
14784	104.886597
14785	223.532394
14786	80.578705

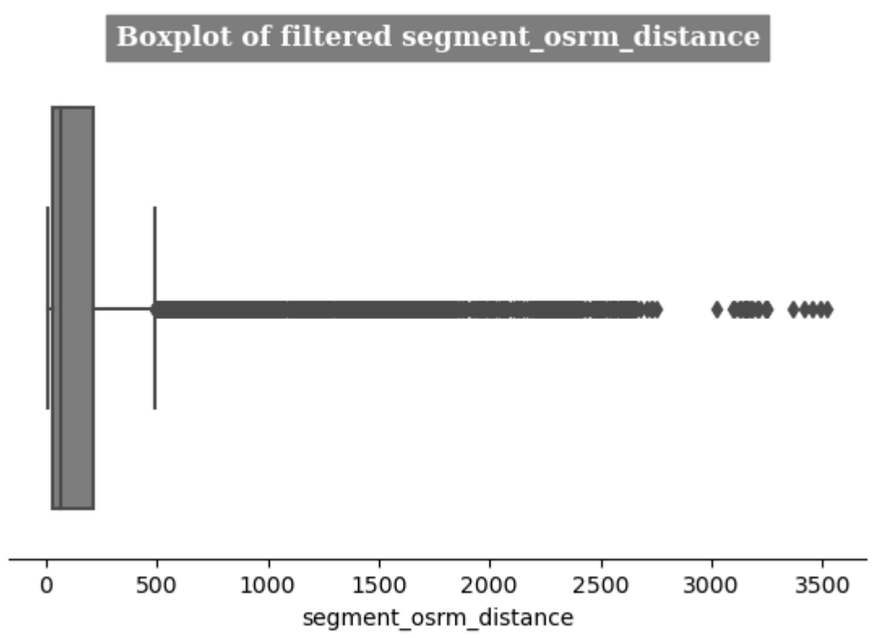
14787 rows × 1 columns

`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 × 1 columns





	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 × 1 columns

```
Clipped data of segment_actual_time_sum
```

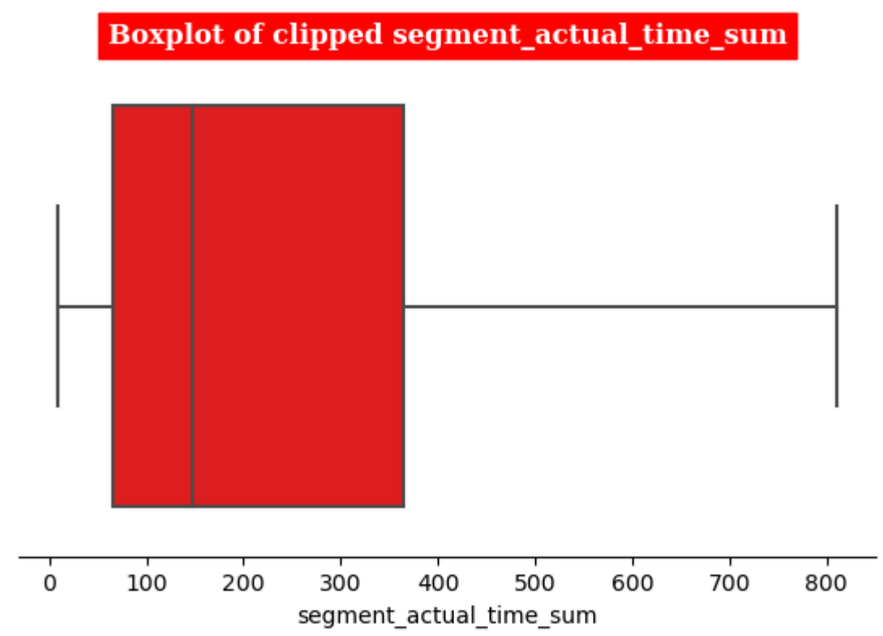
	segment_actual_time_sum
0	811.0
1	141.0
2	811.0
3	59.0
4	340.0
...	...
14782	82.0
14783	21.0
14784	281.0
14785	258.0
14786	274.0

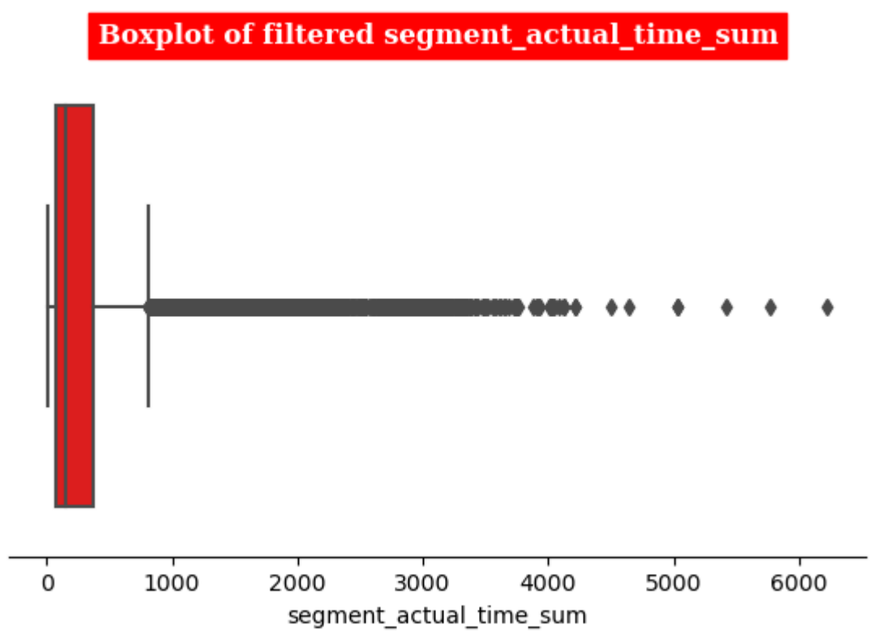
14787 rows × 1 columns

```
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 × 1 columns





	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 × 1 columns

```
Clipped data of segment_osrm_time_sum
```

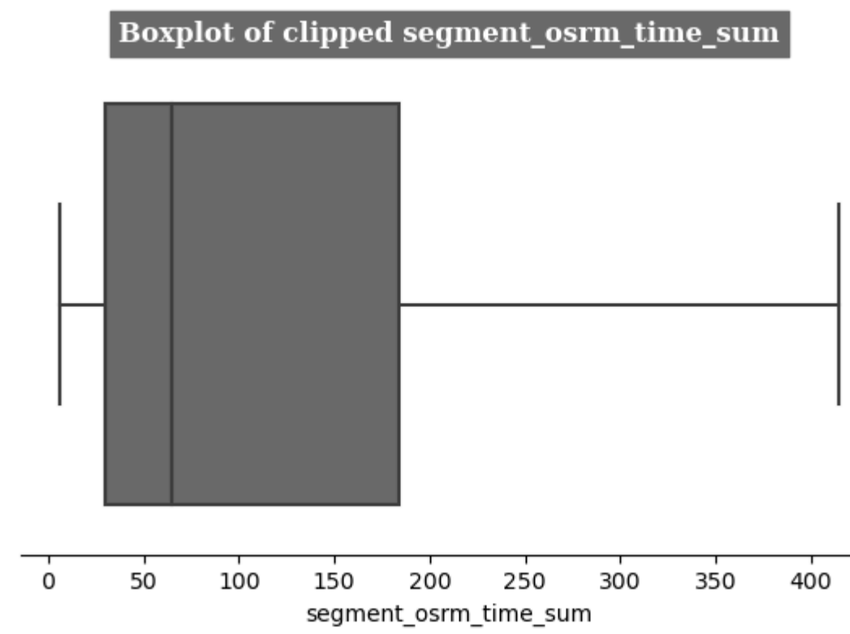
	segment_osrm_time_sum
0	415.0
1	65.0
2	415.0
3	16.0
4	115.0
...	...
14782	62.0
14783	11.0
14784	88.0
14785	221.0
14786	67.0

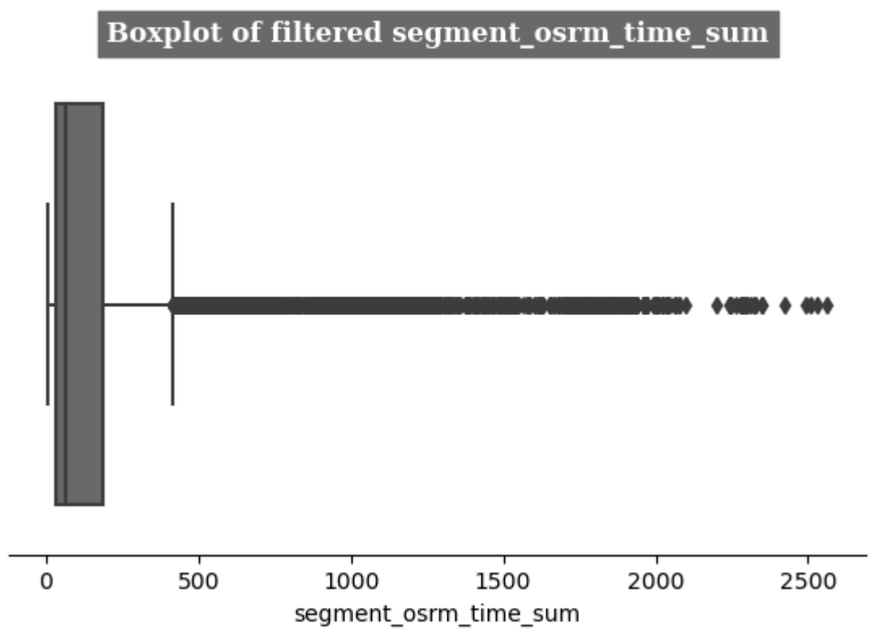
14787 rows × 1 columns

```
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 × 1 columns





	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 × 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

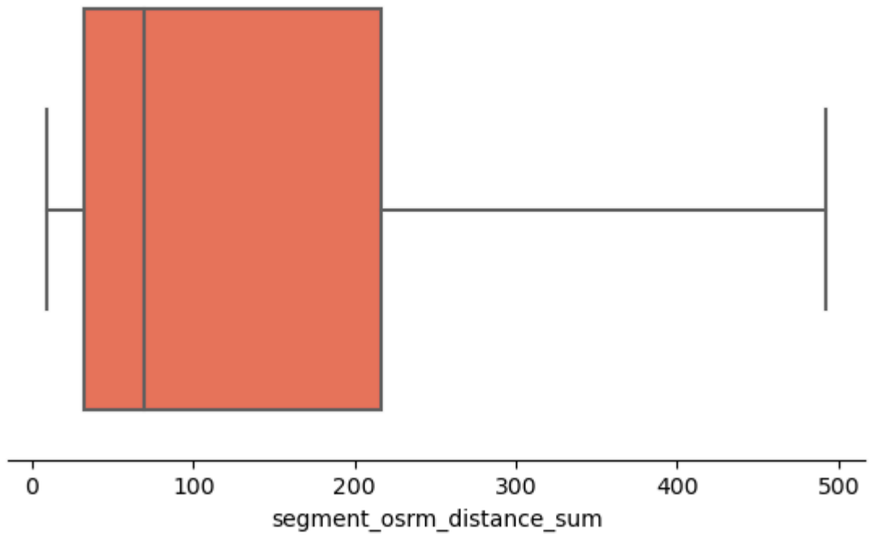
14787 rows × 1 columns

```
Filtered data of segment_osrm_distance_sum
```

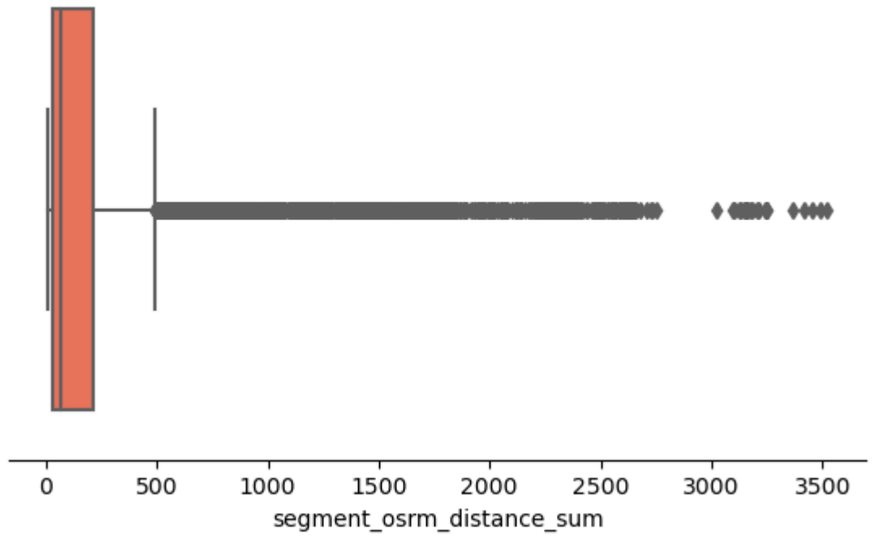
	segment_osrm_distance_sum
0	1320.473267
1	84.189400
2	2545.267822
3	19.876600
4	146.791901
...	...
14782	64.855103
14783	16.088299
14784	104.886597
14785	223.532394
14786	80.578705

14787 rows × 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.

In [135…
```
num_df = numerical_columns.copy()
num_df
```

Out[135]:

	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_tin
0	37.668497	2259.0	824.732849	1562.0	717.0	991.352295	1548.0	1008.0	1320.473267	1548.0	
1	3.026865	180.0	73.186905	143.0	68.0	85.111000	141.0	65.0	84.189400	141.0	
2	65.572709	3933.0	1927.404297	3347.0	1740.0	2354.066650	3308.0	1941.0	2545.267822	3308.0	
3	1.674916	100.0	17.175274	59.0	15.0	19.680000	59.0	16.0	19.876600	59.0	
4	11.972484	717.0	127.448502	341.0	117.0	146.791794	340.0	115.0	146.791901	340.0	
...	...	...	...	...	...	...	...	...	...	...	
14782	4.300482	257.0	57.762333	83.0	62.0	73.462997	82.0	62.0	64.855103	82.0	
14783	1.009842	60.0	15.513784	21.0	12.0	16.088200	21.0	11.0	16.088299	21.0	
14784	7.035331	421.0	38.684837	282.0	48.0	58.903702	281.0	88.0	104.886597	281.0	
14785	5.808548	347.0	134.723831	264.0	179.0	171.110306	258.0	221.0	223.532394	258.0	
14786	5.906793	353.0	66.081528	275.0	68.0	80.578705	274.0	67.0	80.578705	274.0	

14787 rows × 12 columns

In [136…
```
num_cols
```

Out[136]:
```
['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']
```

In [137…
```
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	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_tir
0	37.668497	543.285302	543.285302	543.285302	543.285302	543.285302	543.285302	543.285302	543.285302	543.285302	543
1	3.026865	180.000000	73.186905	143.000000	68.000000	85.111000	141.000000	65.000000	84.189400	141.000000	65
2	65.572709	543.285302	543.285302	543.285302	543.285302	543.285302	543.285302	543.285302	543.285302	543.285302	543
3	1.674916	100.000000	17.175274	59.000000	15.000000	19.680000	59.000000	16.000000	19.876600	59.000000	16
4	11.972484	543.285302	127.448502	341.000000	117.000000	146.791794	340.000000	115.000000	146.791901	340.000000	115
...	...	...	...	...	...	...	...	...	...	...	
14782	4.300482	257.000000	57.762333	83.000000	62.000000	73.462997	82.000000	62.000000	64.855103	82.000000	62
14783	1.009842	60.000000	15.513784	21.000000	12.000000	16.088200	21.000000	11.000000	16.088299	21.000000	11
14784	7.035331	421.000000	38.684837	282.000000	48.000000	58.903702	281.000000	88.000000	104.886597	281.000000	88
14785	5.808548	347.000000	134.723831	264.000000	179.000000	171.110306	258.000000	221.000000	223.532394	258.000000	221
14786	5.906793	353.000000	66.081528	275.000000	68.000000	80.578705	274.000000	67.000000	80.578705	274.000000	67

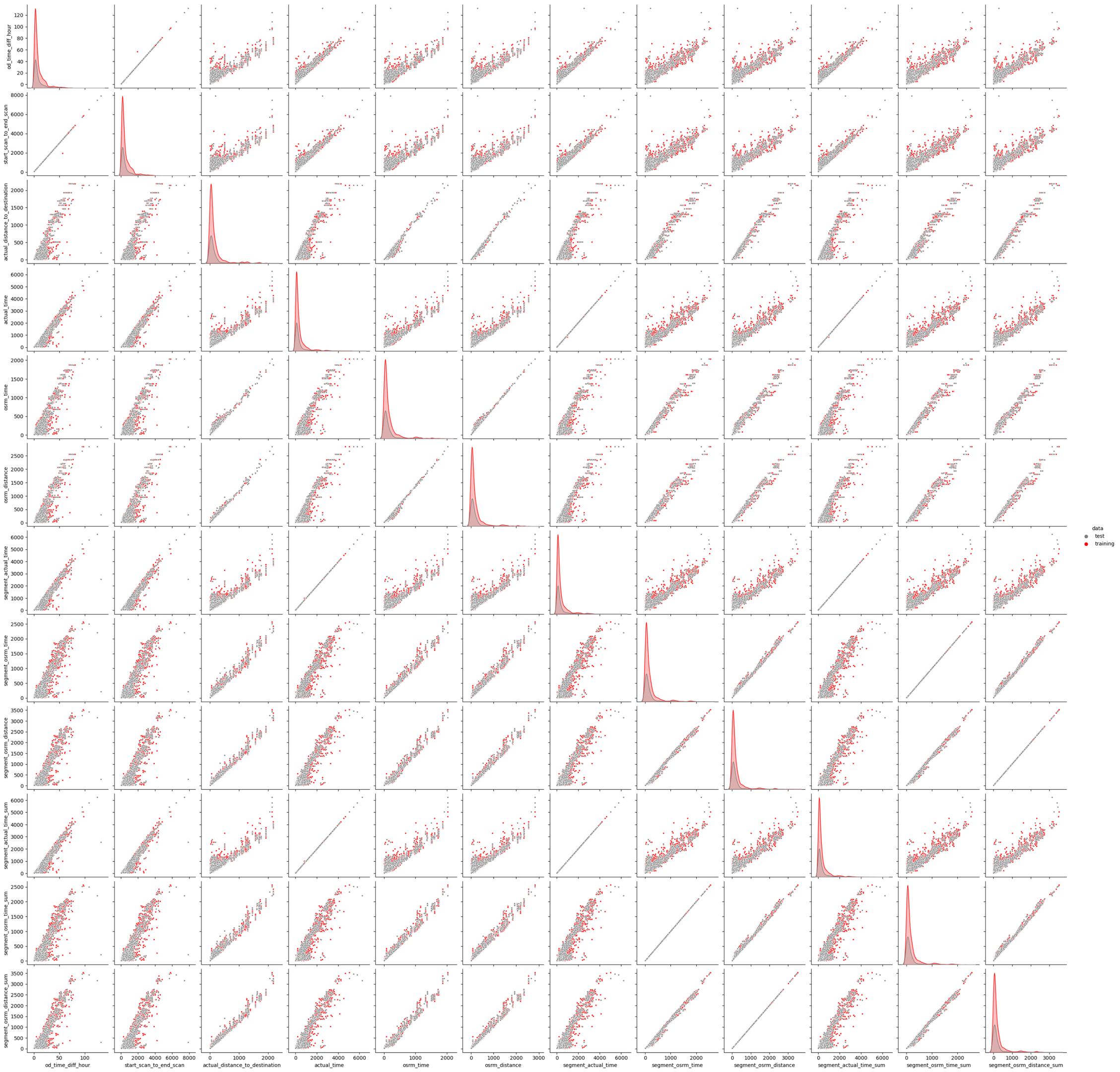
14787 rows × 12 columns

	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_tin
0	37.668497	2259.0	824.732849	1562.0	717.0	991.352295	1548.0	1008.0	1320.473267	1548.0	
1	3.026865	180.0	73.186905	143.0	68.0	85.111000	141.0	65.0	84.189400	141.0	
2	65.572709	3933.0	1927.404297	3347.0	1740.0	2354.066650	3308.0	1941.0	2545.267822	3308.0	
3	1.674916	100.0	17.175274	59.0	15.0	19.680000	59.0	16.0	19.876600	59.0	
4	11.972484	717.0	127.448502	341.0	117.0	146.791794	340.0	115.0	146.791901	340.0	
...	...	...	...	...	...	...	...	...	...	...	
14782	4.300482	257.0	57.762333	83.0	62.0	73.462997	82.0	62.0	64.855103	82.0	
14783	1.009842	60.0	15.513784	21.0	12.0	16.088200	21.0	11.0	16.088299	21.0	
14784	7.035331	421.0	38.684837	282.0	48.0	58.903702	281.0	88.0	104.886597	281.0	
14785	5.808548	347.0	134.723831	264.0	179.0	171.110306	258.0	221.0	223.532394	258.0	
14786	5.906793	353.0	66.081528	275.0	68.0	80.578705	274.0	67.0	80.578705	274.0	

14787 rows × 12 columns

In [138…

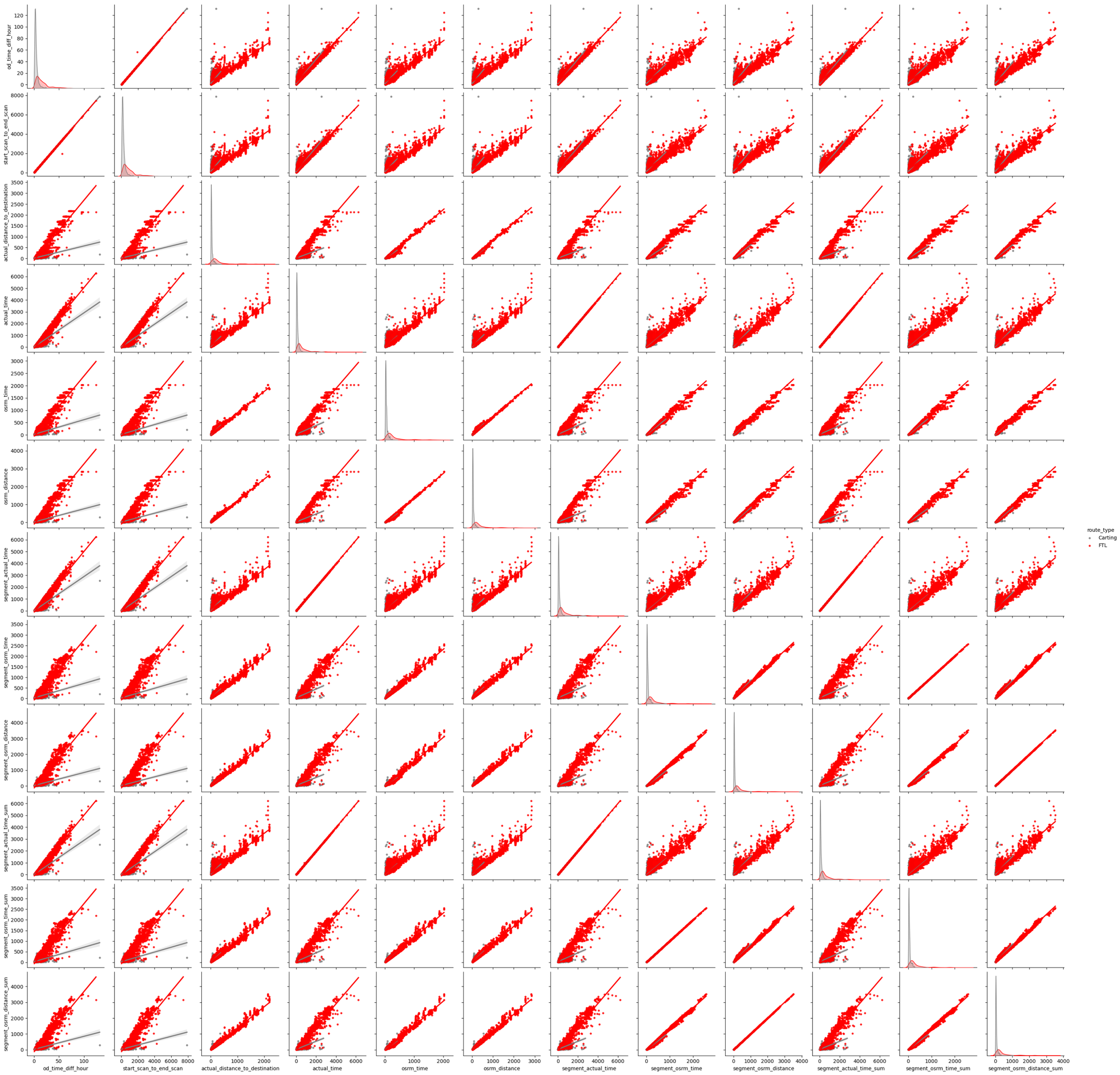
```
plt.figure(figsize=(14,0.05))
plt.axis('off')
plt.title(f' Pairplot Analysis',fontfamily='serif',fontweight='bold',fontsize=15,backgroundcolor='crimson',color='w')
sns.pairplot(data = trip_df,vars = num_cols,hue='data',markers = '.',palette=cp)
plt.show()
```



In [139…

```
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



In [140…

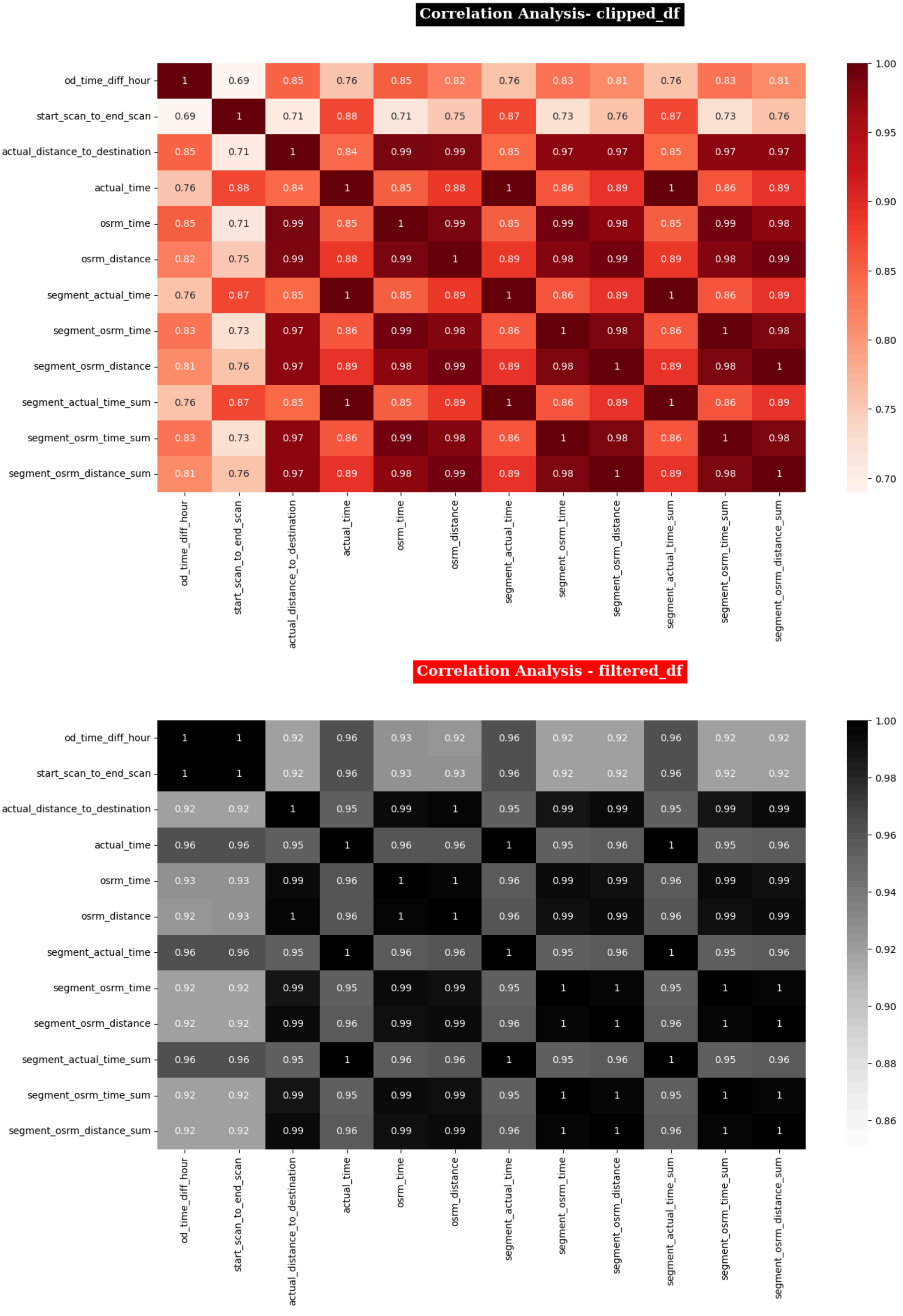
```
clipped_df_corr = clipped_num_df.corr()
clipped_df_corr

filtered_df_corr = filtered_num_df.corr()
filtered_df_corr
```

Out[140]:

	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_
od_time_diff_hour	1.000000	0.999837	0.918644	0.961223	0.926973	0.924683	0.961288	0.918921	0.919665	0.96
start_scan_to_end_scan	0.999837	1.000000	0.919159	0.961612	0.927471	0.925205	0.961634	0.919429	0.920191	0.96
actual_distance_to_destination	0.918644	0.919159	1.000000	0.953920	0.993568	0.997268	0.952987	0.987542	0.993068	0.95
actual_time	0.961223	0.961612	0.953920	1.000000	0.958781	0.959398	0.999989	0.954044	0.957151	0.99
osrm_time	0.926973	0.927471	0.993568	0.958781	1.000000	0.997588	0.957955	0.993263	0.991624	0.95
osrm_distance	0.924683	0.925205	0.997268	0.959398	0.997588	1.000000	0.958540	0.991802	0.994712	0.95
segment_actual_time	0.961288	0.961634	0.952987	0.999989	0.957955	0.958540	1.000000	0.953214	0.956293	1.00
segment_osrm_time	0.918921	0.919429	0.987542	0.954044	0.993263	0.991802	0.953214	1.000000	0.996098	0.95
segment_osrm_distance	0.919665	0.920191	0.993068	0.957151	0.991624	0.994712	0.956293	0.996098	1.000000	0.95
segment_actual_time_sum	0.961288	0.961634	0.952987	0.999989	0.957955	0.958540	1.000000	0.953214	0.956293	1.00
segment_osrm_time_sum	0.918921	0.919429	0.987542	0.954044	0.993263	0.991802	0.953214	1.000000	0.996098	0.95
segment_osrm_distance_sum	0.919665	0.920191	0.993068	0.957151	0.991624	0.994712	0.956293	0.996098	1.000000	0.95

In [145…

```
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()
```



🏷️ Insights:

- Very High Correlation exists between all the numerical columns.

In [254…

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

Out[254]:
```
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***.

1️⃣ 🚀 one-hot encoding

In [146…
```
trip_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14787 entries, 0 to 14786
Data columns (total 37 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   trip_uuid                       14787 non-null  object
 1   data                            14787 non-null  category
 2   route_type                      14787 non-null  category
 3   od_start_time                   14787 non-null  datetime64[ns]
 4   od_end_time                     14787 non-null  datetime64[ns]
 5   od_time_diff_hour               14787 non-null  float64
 6   trip_creation_time              14787 non-null  datetime64[ns]
 7   trip_creation_month             14787 non-null  int32
 8   trip_creation_year              14787 non-null  int32
 9   trip_creation_day               14787 non-null  int32
 10  trip_creation_hour              14787 non-null  int32
 11  trip_creation_weekday           14787 non-null  int32
 12  trip_creation_week              14787 non-null  UInt32
 13  start_scan_to_end_scan          14787 non-null  float32
 14  actual_distance_to_destination  14787 non-null  float32
 15  actual_time                     14787 non-null  float32
 16  osrm_time                       14787 non-null  float32
 17  osrm_distance                   14787 non-null  float32
 18  segment_actual_time             14787 non-null  float32
 19  segment_osrm_time               14787 non-null  float32
 20  segment_osrm_distance           14787 non-null  float32
 21  segment_actual_time_sum         14787 non-null  float32
 22  segment_osrm_time_sum           14787 non-null  float32
 23  segment_osrm_distance_sum       14787 non-null  float32
 24  source_name                     14787 non-null  object
 25  source_city                     14787 non-null  object
 26  source_state                    14787 non-null  object
 27  source_place                    14787 non-null  object
 28  destination_name                14787 non-null  object
 29  destination_city                14787 non-null  object
 30  destination_state               14787 non-null  object
 31  destination_place               14787 non-null  object
 32  corridor                        14787 non-null  object
 33  state_corridor                  14787 non-null  object
 34  city_corridor                   14787 non-null  object
 35  trip_creation_day_week          14787 non-null  object
 36  trip_creation_dayofdate         14787 non-null  int32
dtypes: UInt32(1), category(2), datetime64[ns](3), float32(11), float64(1), int32(6), object(13)
memory usage: 3.0+ MB
```

In [147…
```
categorical_cols = ['data','route_type']
```

In [149…
```
# 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 × 4 columns

Out[149]:

	trip_uuid	data	route_type	od_start_time	od_end_time	od_time_diff_hour	trip_creation_time	trip_creation_month	trip_creation_year	trip_creation_day	trip_creation_hour	trip_creation_weekday	trip_creatic
0	trip-153671041653548748	training	FTL	2018-09-12 16:39:46.858469	2018-09-12 16:39:46.858469	37.668497	2018-09-12 00:00:16.535741	9	2018	12	0	2	
1	trip-153671042288605164	training	Carting	2018-09-12 02:03:09.655591	2018-09-12 02:03:09.655591	3.026865	2018-09-12 00:00:22.886430	9	2018	12	0	2	
2	trip-153671043369099517	training	FTL	2018-09-14 03:40:17.106733	2018-09-14 03:40:17.106733	65.572709	2018-09-12 00:00:33.691250	9	2018	12	0	2	
3	trip-153671046011330457	training	Carting	2018-09-12 00:01:00.113710	2018-09-12 01:41:29.809822	1.674916	2018-09-12 00:01:00.113710	9	2018	12	0	2	
4	trip-153671052974046625	training	FTL	2018-09-12 00:02:09.740725	2018-09-12 03:54:43.114421	11.972484	2018-09-12 00:02:09.740725	9	2018	12	0	2	
...	...	...	...	...	...	...	...	...	...	...	...	...	...
14782	trip-153861095625827784	test	Carting	2018-10-03 23:55:56.258533	2018-10-04 06:41:25.409035	4.300482	2018-10-03 23:55:56.258533	10	2018	3	23	2	
14783	trip-153861104386292051	test	Carting	2018-10-03 23:57:23.863155	2018-10-04 00:57:59.294434	1.009842	2018-10-03 23:57:23.863155	10	2018	3	23	2	
14784	trip-153861106442901555	test	Carting	2018-10-04 02:51:27.075797	2018-10-04 02:51:27.075797	7.035331	2018-10-03 23:57:44.429324	10	2018	3	23	2	
14785	trip-153861115439069069	test	Carting	2018-10-03 23:59:14.390954	2018-10-04 02:29:04.272194	5.808548	2018-10-03 23:59:14.390954	10	2018	3	23	2	
14786	trip-153861118270144424	test	FTL	2018-10-04 03:58:40.726547	2018-10-04 03:58:40.726547	5.906793	2018-10-03 23:59:42.701692	10	2018	3	23	2	

14787 rows × 41 columns

0 - 1 Minmax scaler

- Most appropriate since the data is not gaussian

In [150…

```
# 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
```

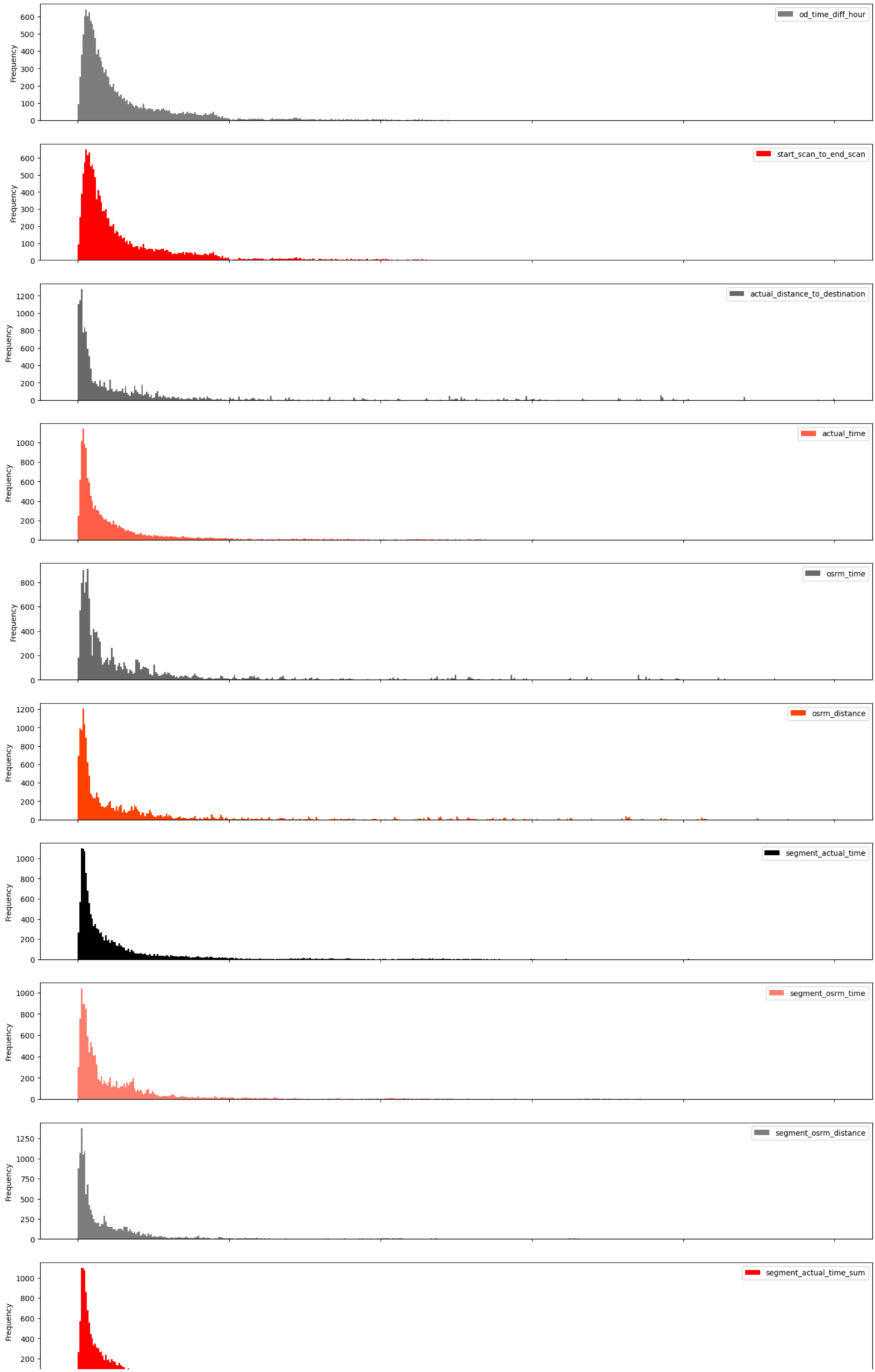
Out[150]:

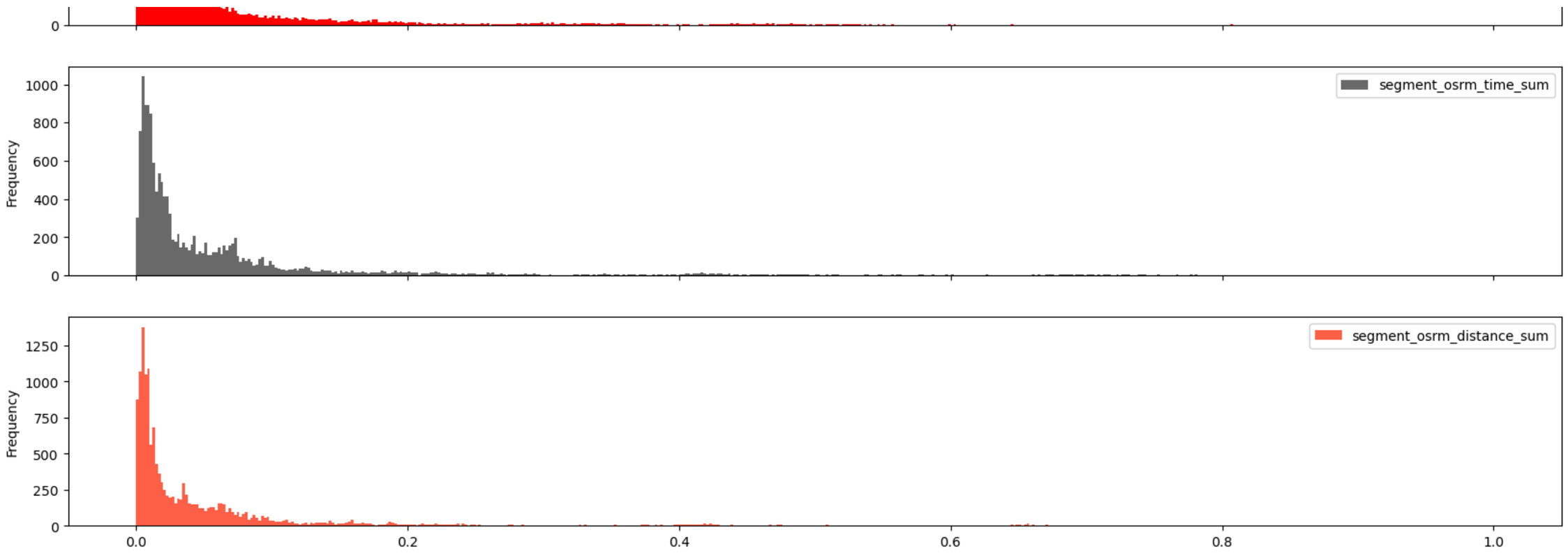
	od_time_diff_hour	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_time	segment_osrm_time	segment_osrm_distance	segment_actual_time_sum	segment_osrm_tin
0	0.284016	0.283937	0.374613	0.248242	0.350938	0.346972	0.247388	0.391712	0.373134	0.247388	0
1	0.020082	0.019937	0.029476	0.021419	0.030602	0.026859	0.021218	0.023065	0.021373	0.021218	0
2	0.496617	0.496508	0.880999	0.533568	0.855874	0.828325	0.530301	0.756450	0.721625	0.530301	0
3	0.009782	0.009778	0.003753	0.007992	0.004442	0.003747	0.008037	0.003909	0.003074	0.008037	0
4	0.088239	0.088127	0.054395	0.053069	0.054788	0.048647	0.053207	0.042611	0.039185	0.053207	0
...	...	...	...	...	...	...	...	...	...	...	...
14782	0.029786	0.029714	0.022392	0.011829	0.027641	0.022745	0.011734	0.021892	0.015872	0.011734	0
14783	0.004715	0.004698	0.002990	0.001918	0.002962	0.002478	0.001929	0.001955	0.001996	0.001929	0
14784	0.050623	0.050540	0.013631	0.043638	0.020731	0.017602	0.043723	0.032056	0.027262	0.043723	0
14785	0.041276	0.041143	0.057736	0.040761	0.085390	0.057237	0.040026	0.084050	0.061020	0.040026	0
14786	0.042024	0.041905	0.026213	0.042519	0.030602	0.025258	0.042598	0.023847	0.020346	0.042598	0

14787 rows × 12 columns

In [155…

```
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()
```


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
Frequency



In [156…

```
# 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
```

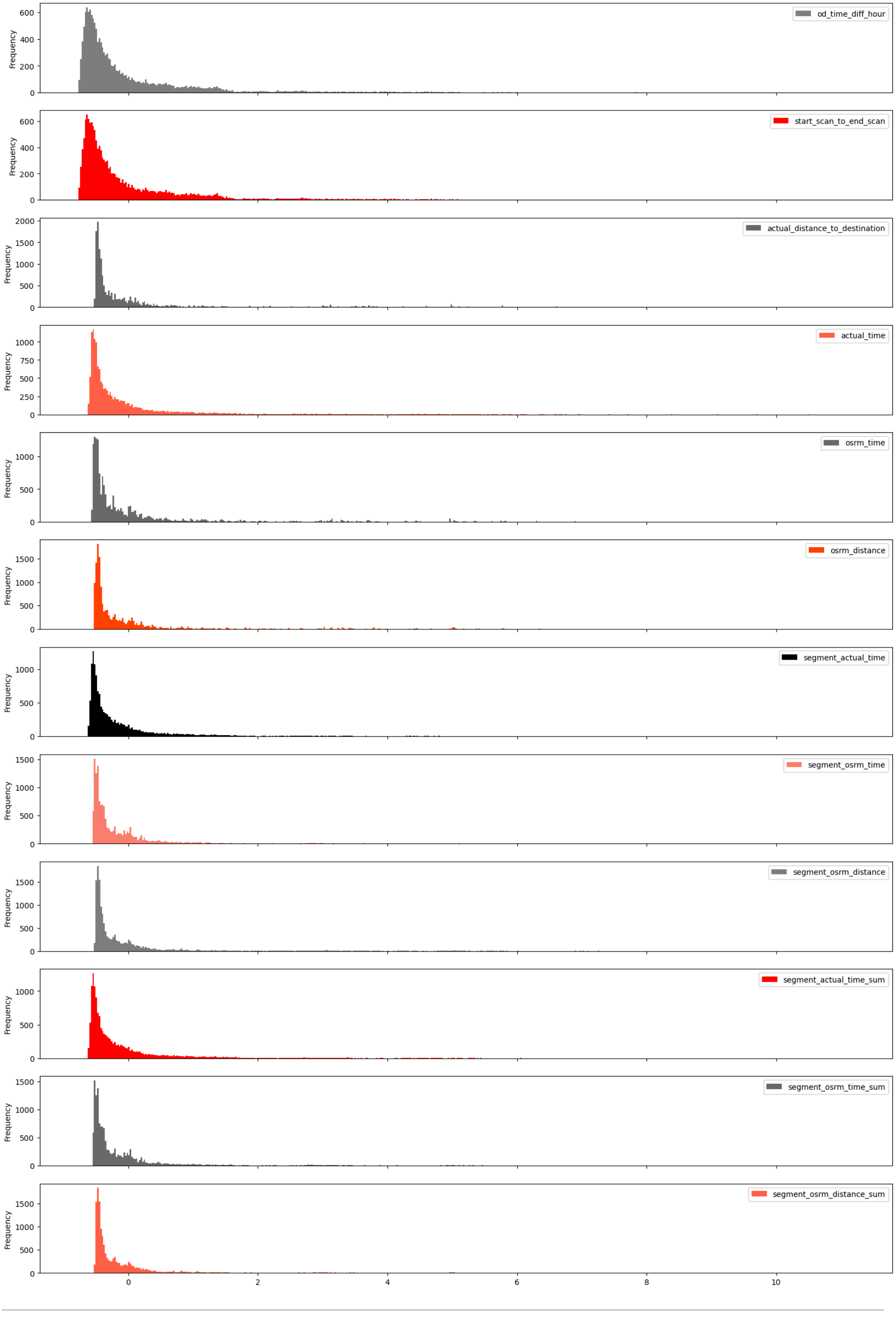
Out[156]:

	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_tim
0	2.625886	2.627598	2.162548	2.147277	2.048290	2.125107	2.147833	2.629714	2.633597	2.147833	2
1	-0.529518	-0.530859	-0.297563	-0.379887	-0.342571	-0.320538	-0.381163	-0.367090	-0.332307	-0.381163	-0
2	5.167598	5.170772	5.772034	5.326268	5.816936	5.802622	5.311326	5.594737	5.571936	5.311326	5
3	-0.652664	-0.652397	-0.480911	-0.529486	-0.537818	-0.497115	-0.528553	-0.522809	-0.486596	-0.528553	-0
4	0.285312	0.284962	-0.119943	-0.027259	-0.162059	-0.154082	-0.023473	-0.208192	-0.182120	-0.023473	-0
...	...	...	...	...	...	...	...	...	...	...	
14782	-0.413508	-0.413880	-0.348054	-0.486744	-0.364674	-0.351972	-0.487212	-0.376623	-0.378690	-0.487212	-0
14783	-0.713243	-0.713166	-0.486350	-0.597162	-0.548870	-0.506808	-0.596856	-0.538699	-0.495684	-0.596856	-0
14784	-0.164399	-0.164728	-0.410502	-0.132335	-0.416249	-0.391263	-0.129522	-0.293997	-0.282653	-0.129522	-0
14785	-0.276143	-0.277150	-0.096128	-0.164392	0.066344	-0.088455	-0.170863	0.128670	0.001984	-0.170863	0
14786	-0.267194	-0.268034	-0.320822	-0.144802	-0.342571	-0.332769	-0.142104	-0.360734	-0.340969	-0.142104	-0

14787 rows × 12 columns

In [157…

```
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()
```



☝ 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 (Ho)** - There is no significant difference in the mean values between column1 and column2
> H_{o}: $μ_{col1}$ = $μ_{col2}$
>
> **Alternate Hypothesis (Ha)** - There is a significant difference in the mean values between column1 and column2
> H_{a}: $μ_{col1}$!= $μ_{col2}$

📌 ***STEP-2*** : Checking for basic assumpitons 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 Ho.

- 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 Ho
>
> **p-val > alpha** : Accept Ho

In [198…

```
# 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_tranformation(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)
```

In [207…

```
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()
```

In [203…

```
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 ""
```

In [216…

```
## 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 Ho")
        print(f'There is NO significant difference in the Mean values of {name1} and {name2}')

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

    return ""
```

In [227…

```
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.

In [158…

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

Out[158]:

	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_tim
4578	10.118006	543.285302	220.068207	353.0	221.0	249.271805	351.0	238.0	272.674194	351.0	
176	1.358135	81.000000	9.083277	28.0	11.0	14.245600	28.0	11.0	14.245600	28.0	
505	6.646569	398.000000	101.146736	259.0	98.0	130.815598	257.0	115.0	130.997910	257.0	

In [219…

```
clipped_num_df[['actual_time','osrm_time']].describe().T
```

Out[219]:

	count	mean	std	min	25%	50%	75%	max
actual_time	14787.0	224.212577	185.922840	9.0	67.0	148.0	367.0	543.285302
osrm_time	14787.0	128.190912	150.301267	6.0	29.0	60.0	168.0	543.285302

In [167…
```
filtered_num_df[['actual_time','osrm_time']].describe().T
```

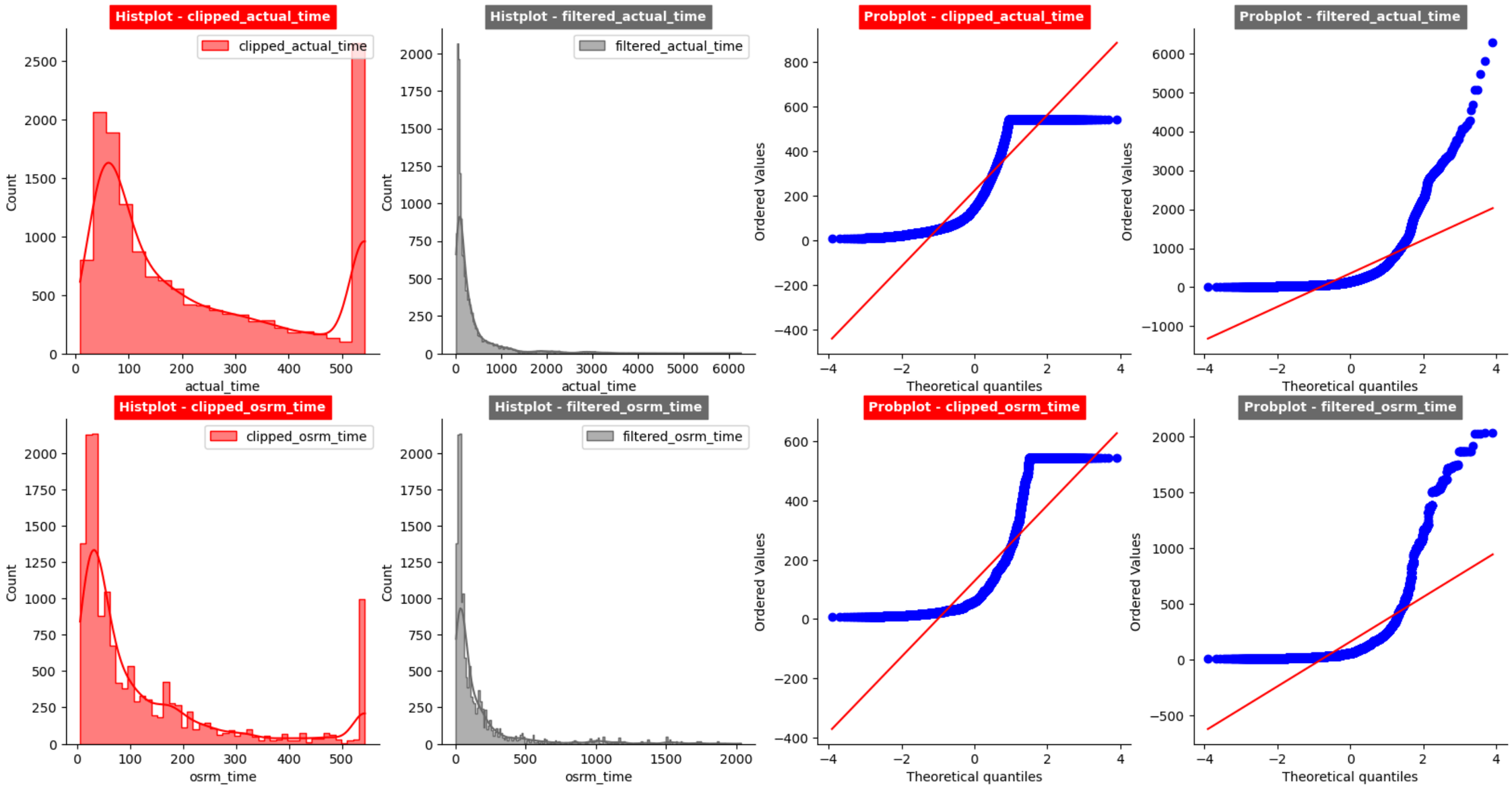
Out[167]:

	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

In [169…
```
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']
```

In [228…
```
normality_plots('clipped_actual_time','clipped_osrm_time','filtered_actual_time','filtered_osrm_time',actual_time,osrm_time,fil_actual_time,fil_osrm_time)
```

Normality check - Histplot & QQ(prob)plot



In [213…
```
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.

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

In [204…

```
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

--------------------------------------------------

''
```

Out[204]:

Wilcoxon signed rank test:

In [214…

```
## 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
```

In [215…

```
## 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
```

In [218…

```
### 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_{o}: $μ_{Aggregated-actual-time}$!= $μ_{Aggregated-osrm-time}$
>
> Further, it is found that `The Aggregated Actual_time is More than the Aggregated OSRM_time` through ***Wilcoxon signed Rank*** test.
>
> - H_{o}: $μ_{Aggregated-actual-time}$ > $μ_{Aggregated-osrm-time}$

⚡ Actual_time aggregated value and Segment actual time aggregated value.

In [220…
```
clipped_num_df.sample()
```

Out[220]:

	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_tin
11839	4.644768	278.0	46.165558	104.0	63.0	75.968498	101.0	61.0	62.8657	101.0	

In [221…
```
clipped_num_df[['actual_time','segment_actual_time']].describe().T
```

Out[221]:

	count	mean	std	min	25%	50%	75%	max
actual_time	14787.0	224.212577	185.922840	9.0	67.0	148.0	367.0	543.285302
segment_actual_time	14787.0	222.904643	185.797003	9.0	66.0	147.0	364.0	543.285302

In [222…
```
filtered_num_df[['actual_time','segment_actual_time']].describe().T
```

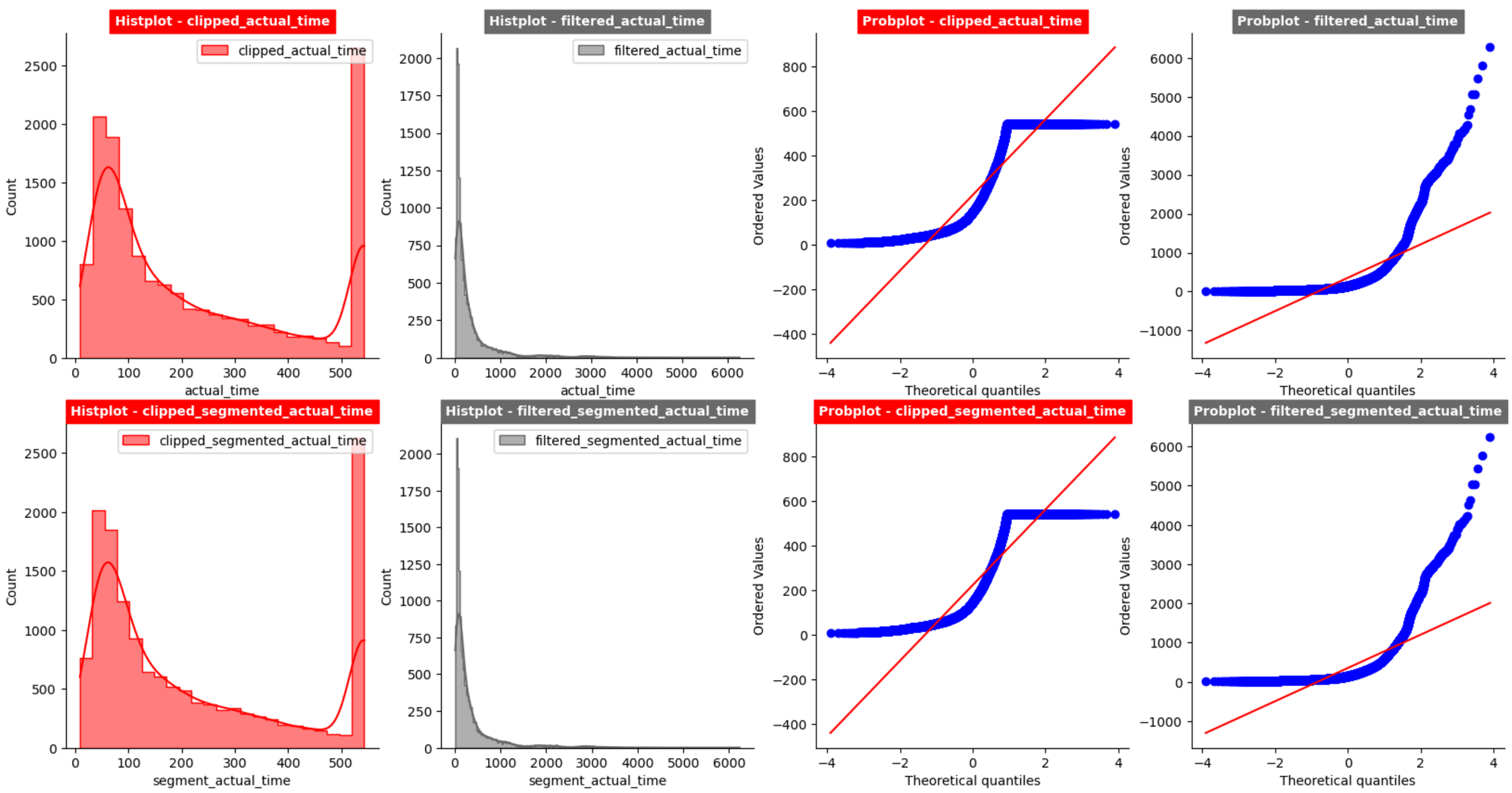
Out[222]:

	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
segment_actual_time	14787.0	353.059174	556.364441	9.0	66.0	147.0	364.0	6230.0

In [223…
```
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']
```

In [229…
```
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



In [230…
```
col_names= ["clipped_actual_time","clipped_segmented_actual_time","filtered_actual_time","filtered_segmented_actual_time"]
cols = [clipped_actual_time,clipped_segmented_actual_time,filtered_actual_time,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.

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

In [232…]

```
levene_test("clipped_actual_time","clipped_segmented_actual_time",clipped_actual_time,clipped_segmented_actual_time),
levene_test("filtered_actual_time","filtered_segmented_actual_time",filtered_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

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

Out[232]:

```
''
```

In [231…]

```
### 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 Ho
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 Ho
There is NO significant difference in the Mean values of filtered_actual_time and filtered_segmented_actual_time

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

🏷️ Insights:

> Even thought 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_{o}: $μ_{Aggregated-actual-time}$ = $μ_{Segmented-actual-time}$

⚡ OSRM distance aggregated value and segment OSRM distance aggregated value.

In [245…]

```
filtered_num_df.sample()
```

Out[245]:

	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_tim
3944	5.694592	341.0	88.352287	156.0	71.0	101.823898	155.0	70.0	101.823898	155.0	

In [246…
```
clipped_num_df[['osrm_distance','segment_osrm_distance']].describe().T
```

Out[246]:

	count	mean	std	min	25%	50%	75%	max
osrm_distance	14787.0	144.551531	162.880435	9.0729	30.75690	65.302795	206.644203	543.285302
segment_osrm_distance	14787.0	150.959153	165.473080	9.0729	32.57885	69.784203	216.560608	543.285302

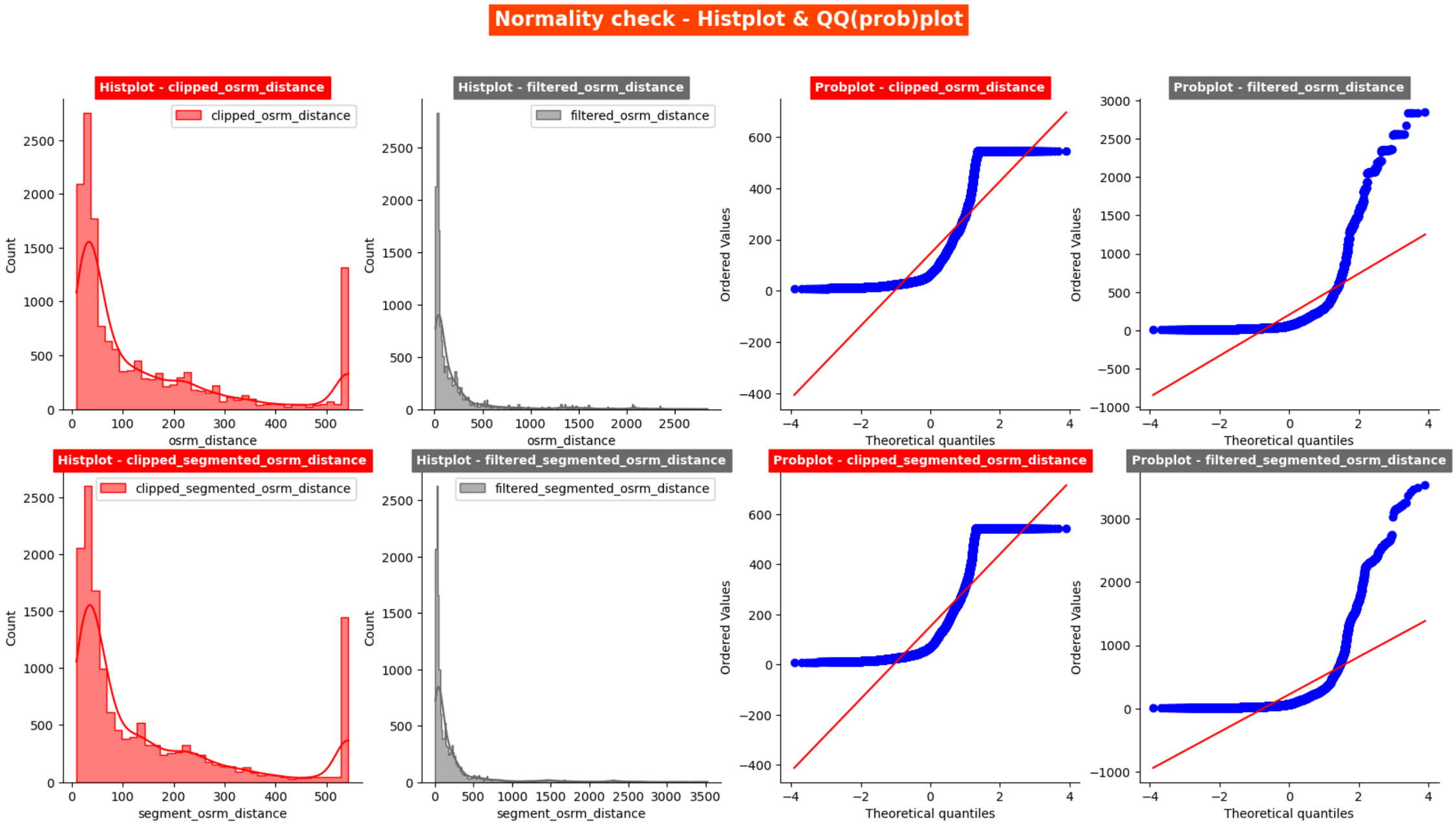
In [247…
```
filtered_num_df[['osrm_distance','segment_osrm_distance']].describe().T
```

Out[247]:

	count	mean	std	min	25%	50%	75%	max
osrm_distance	14787.0	203.887405	370.565460	9.0729	30.75690	65.302795	206.644203	2840.081055
segment_osrm_distance	14787.0	222.705444	416.845642	9.0729	32.57885	69.784203	216.560608	3523.632324

In [248…
```
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']
```

In [249…
```
normality_plots("clipped_osrm_distance","clipped_segmented_osrm_distance","filtered_osrm_distance","filtered_segmented_osrm_distance",
                clipped_osrm_distance,clipped_segmented_osrm_distance,filtered_osrm_distance,filtered_segmented_osrm_distance)
```



In [250…
```
col_names= ["clipped_osrm_distance","clipped_segmented_osrm_distance","filtered_osrm_distance","filtered_segmented_osrm_distance"]
cols = [clipped_osrm_distance,clipped_segmented_osrm_distance,filtered_osrm_distance,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.

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

In [251…

```
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

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

Out[251]:

```
''
```

In [252…

```
### 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_{o}: $μ_{Aggregated-osrm-distance}$!= $μ_{Segmented-osrm-distance-aggregated}$

⚡ OSRM time aggregated value and segment OSRM time aggregated value.

In [233…

```
filtered_num_df.sample()
```

Out[233]:

	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_
113	3.763914	225.0	45.959438	140.0	57.0	54.921398	138.0	66.0	64.504799	138.0	

In [234…
```
clipped_num_df[['osrm_time','segment_osrm_time']].describe().T
```

Out[234]:

	count	mean	std	min	25%	50%	75%	max
osrm_time	14787.0	128.190912	150.301267	6.0	29.0	60.0	168.0	543.285302
segment_osrm_time	14787.0	136.843818	155.422255	6.0	30.0	65.0	184.0	543.285302

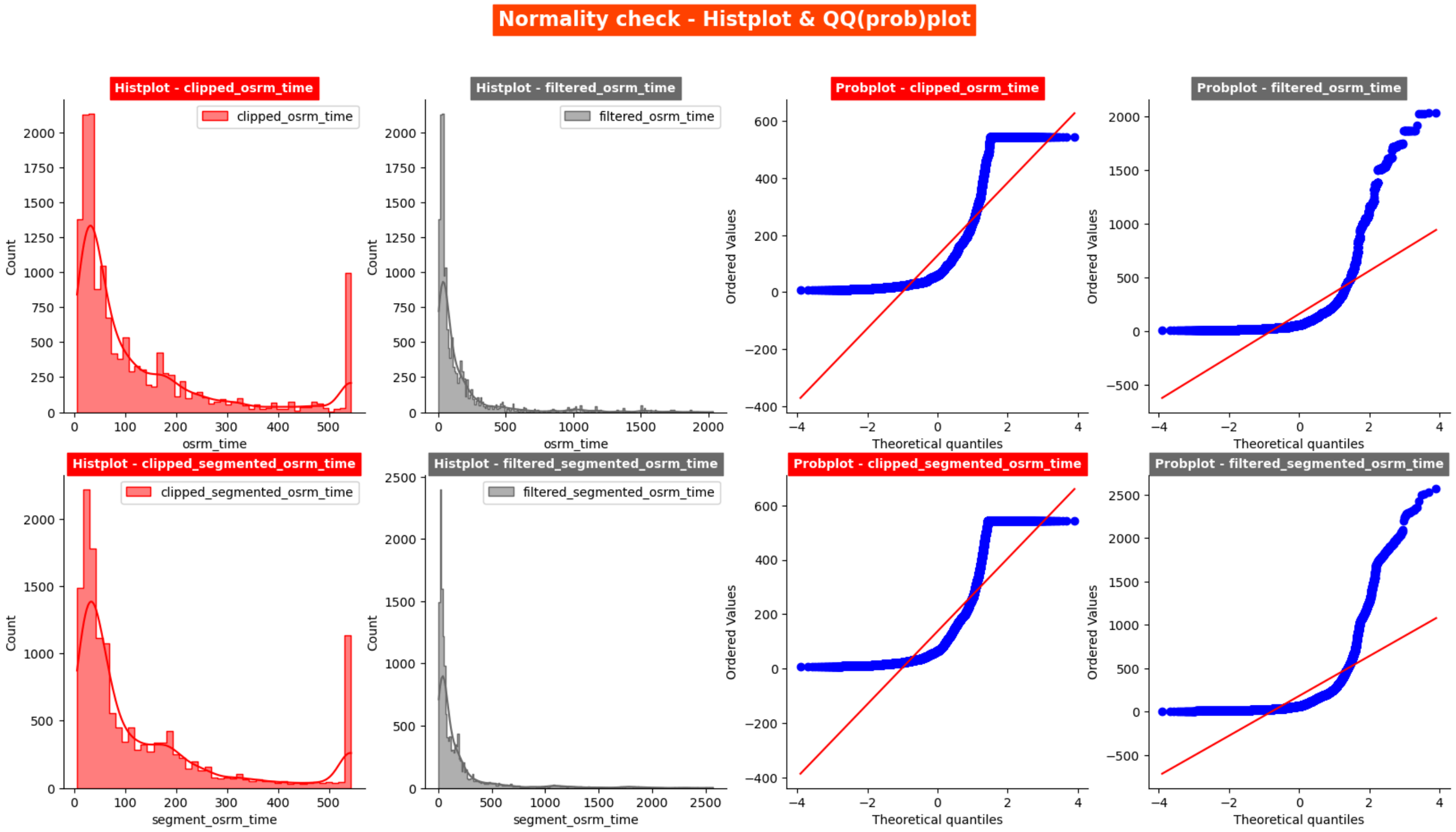
In [235…
```
filtered_num_df[['osrm_time','segment_osrm_time']].describe().T
```

Out[235]:

	count	mean	std	min	25%	50%	75%	max
osrm_time	14787.0	160.990936	271.459229	6.0	29.0	60.0	168.0	2032.0
segment_osrm_time	14787.0	180.511597	314.678741	6.0	30.0	65.0	184.0	2564.0

In [240…
```
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']
```

In [241…
```
normality_plots("clipped_osrm_time","clipped_segmented_osrm_time","filtered_osrm_time","filtered_segmented_osrm_time",
                clipped_osrm_time,clipped_segmented_osrm_time,filtered_osrm_time,filtered_segmented_osrm_time)
```



In [242…
```
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.

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

In [243…

```
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",filtered_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

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

Out[243]:

```
''
```

In [244…

```
### 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_{o}: $μ_{Aggregated-osrm-time}$!= $μ_{Segmented-osrm-time-aggregated}$

In [292…

```
trip_df.sample()
```

Out[292]:

	trip_uuid	data	route_type	od_start_time	od_end_time	od_time_diff_hour	trip_creation_time	trip_creation_month	trip_creation_year	trip_creation_day	trip_creation_hour	trip_creation_weekday	trip_creatior
8533	trip-153774183943645102	training	Carting	2018-09-24 00:46:07.807847	2018-09-24 07:32:00.833381	9.02261	2018-09-23 22:30:39.436721	9	2018	23	22	6	

In [295…

```
# 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 heavy positively correleated with each other & which is intutive 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
- Thats 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 atates 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.
