Delhivery_EDA_Feature_Eng

April 18, 2025

1 Business Case: Delhivery - Feature Engineering

About Delhivery:

Delhivery is the largest and fastest-growing fully integrated player in India by revenue in Fiscal 2021. They aim to build the operating system for commerce, through a combination of world-class infrastructure, logistics operations of the highest quality, and cutting-edge engineering and technology capabilities. The Data team builds intelligence and capabilities using this data that helps them to widen the gap between the quality, efficiency, and profitability of their business versus their competitors.

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

1.1 Importing Required Libraries

[317]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib as mpl
import seaborn as sns
import warnings
import scipy.stats as spy
warnings.simplefilter('ignore')

df=pd.read_csv("/content/delhivery_data.csv")
```

[318]:
```
df.shape
```

[318]:
```
(144867, 24)
```

[319]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
```

```
Data columns (total 24 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144867 non-null  object
 1   trip_creation_time              144867 non-null  object
 2   route_schedule_uuid             144867 non-null  object
 3   route_type                      144867 non-null  object
 4   trip_uuid                       144867 non-null  object
 5   source_center                   144867 non-null  object
 6   source_name                     144574 non-null  object
 7   destination_center              144867 non-null  object
 8   destination_name                144606 non-null  object
 9   od_start_time                   144867 non-null  object
 10  od_end_time                     144867 non-null  object
 11  start_scan_to_end_scan          144867 non-null  float64
 12  is_cutoff                       144867 non-null  bool
 13  cutoff_factor                   144867 non-null  int64
 14  cutoff_timestamp                144867 non-null  object
 15  actual_distance_to_destination  144867 non-null  float64
 16  actual_time                     144867 non-null  float64
 17  osrm_time                       144867 non-null  float64
 18  osrm_distance                   144867 non-null  float64
 19  factor                          144867 non-null  float64
 20  segment_actual_time             144867 non-null  float64
 21  segment_osrm_time               144867 non-null  float64
 22  segment_osrm_distance           144867 non-null  float64
 23  segment_factor                  144867 non-null  float64
dtypes: bool(1), float64(10), int64(1), object(12)
memory usage: 25.6+ MB
```

[320]:
```
df.head(10)
```

[320]:
```
       data          trip_creation_time  \
0  training  2018-09-20 02:35:36.476840
1  training  2018-09-20 02:35:36.476840
2  training  2018-09-20 02:35:36.476840
3  training  2018-09-20 02:35:36.476840
4  training  2018-09-20 02:35:36.476840
5  training  2018-09-20 02:35:36.476840
6  training  2018-09-20 02:35:36.476840
7  training  2018-09-20 02:35:36.476840
8  training  2018-09-20 02:35:36.476840
9  training  2018-09-20 02:35:36.476840

                                 route_schedule_uuid route_type  \
0  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
1  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
```

```
2  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
3  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
4  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
5  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
6  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
7  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
8  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
9  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting

                 trip_uuid source_center                     source_name  \
0  trip-153741093647649320  IND388121AAA     Anand_VUNagar_DC (Gujarat)
1  trip-153741093647649320  IND388121AAA     Anand_VUNagar_DC (Gujarat)
2  trip-153741093647649320  IND388121AAA     Anand_VUNagar_DC (Gujarat)
3  trip-153741093647649320  IND388121AAA     Anand_VUNagar_DC (Gujarat)
4  trip-153741093647649320  IND388121AAA     Anand_VUNagar_DC (Gujarat)
5  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
6  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
7  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
8  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
9  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)

  destination_center               destination_name  \
0       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
1       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
2       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
3       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
4       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
5       IND388320AAA     Anand_Vaghasi_IP (Gujarat)
6       IND388320AAA     Anand_Vaghasi_IP (Gujarat)
7       IND388320AAA     Anand_Vaghasi_IP (Gujarat)
8       IND388320AAA     Anand_Vaghasi_IP (Gujarat)
9       IND388320AAA     Anand_Vaghasi_IP (Gujarat)

                od_start_time  …            cutoff_timestamp  \
0  2018-09-20 03:21:32.418600  …         2018-09-20 04:27:55
1  2018-09-20 03:21:32.418600  …         2018-09-20 04:17:55
2  2018-09-20 03:21:32.418600  …  2018-09-20 04:01:19.505586
3  2018-09-20 03:21:32.418600  …         2018-09-20 03:39:57
4  2018-09-20 03:21:32.418600  …         2018-09-20 03:33:55
5  2018-09-20 04:47:45.236797  …         2018-09-20 06:15:58
6  2018-09-20 04:47:45.236797  …         2018-09-20 05:47:29
7  2018-09-20 04:47:45.236797  …         2018-09-20 05:25:58
8  2018-09-20 04:47:45.236797  …         2018-09-20 05:15:56
9  2018-09-20 04:47:45.236797  …         2018-09-20 04:49:20

  actual_distance_to_destination  actual_time  osrm_time osrm_distance  \
0                      10.435660         14.0       11.0       11.9653
```

```
1                      18.936842        24.0       20.0       21.7243
2                      27.637279        40.0       28.0       32.5395
3                      36.118028        62.0       40.0       45.5620
4                      39.386040        68.0       44.0       54.2181
5                      10.403038        15.0       11.0       12.1171
6                      18.045481        44.0       17.0       21.2890
7                      28.061896        65.0       29.0       35.8252
8                      38.939167        76.0       39.0       47.1900
9                      43.595802       102.0       45.0       53.2334

     factor  segment_actual_time  segment_osrm_time  segment_osrm_distance  \
0  1.272727                 14.0               11.0                11.9653
1  1.200000                 10.0                9.0                 9.7590
2  1.428571                 16.0                7.0                10.8152
3  1.550000                 21.0               12.0                13.0224
4  1.545455                  6.0                5.0                 3.9153
5  1.363636                 15.0               11.0                12.1171
6  2.588235                 28.0                6.0                 9.1719
7  2.241379                 21.0               11.0                14.5362
8  1.948718                 10.0               10.0                11.3648
9  2.266667                 26.0                6.0                 6.0434

   segment_factor
0        1.272727
1        1.111111
2        2.285714
3        1.750000
4        1.200000
5        1.363636
6        4.666667
7        1.909091
8        1.000000
9        4.333333

[10 rows x 24 columns]
```

Dropping Unknown Fields:

[321]:
```python
# Dropping Unknown fields
unknown =␣
 ↪['is_cutoff','cutoff_factor','cutoff_timestamp','factor','segment_factor']
df.drop(columns=unknown,inplace=True)
```

[322]:
```python
# Unique entries in columns

for i in df.columns:
  print(f"Unique Entries in {i} column: {df[i].nunique()}")
```

```
Unique Entries in data column: 2
Unique Entries in trip_creation_time column: 14817
Unique Entries in route_schedule_uuid column: 1504
Unique Entries in route_type column: 2
Unique Entries in trip_uuid column: 14817
Unique Entries in source_center column: 1508
Unique Entries in source_name column: 1498
Unique Entries in destination_center column: 1481
Unique Entries in destination_name column: 1468
Unique Entries in od_start_time column: 26369
Unique Entries in od_end_time column: 26369
Unique Entries in start_scan_to_end_scan column: 1915
Unique Entries in actual_distance_to_destination column: 144515
Unique Entries in actual_time column: 3182
Unique Entries in osrm_time column: 1531
Unique Entries in osrm_distance column: 138046
Unique Entries in segment_actual_time column: 747
Unique Entries in segment_osrm_time column: 214
Unique Entries in segment_osrm_distance column: 113799
```

Converting Data and Route type columns to Category

[323]:
```
# Converting date and route_type column to category columns:

df['data'] = df['data'].astype('category')
df['route_type'] = df['route_type'].astype('category')
```

[324]:
```
float_cols =␣
↪['start_scan_to_end_scan','actual_distance_to_destination','actual_time','osrm_time','osrm_

for i in float_cols:
  print(df[i].max())
```

```
7898.0
1927.4477046975032
4532.0
1686.0
2326.1991000000003
3051.0
1611.0
2191.4037000000003
```

[325]:
```
for i in float_cols:
  df[i] = df[i].astype('float32')
```

Updating date & time columns to datetime datatypes:

[326]:
```python
# Updating date & time columns to datetime data type

datetime_cols = ['trip_creation_time','od_start_time','od_end_time']

for i in datetime_cols:
  df[i] =  pd.to_datetime(df[i])
```

Checking for Null Values in dataframe

[327]:
```python
df.isna().sum()
```

[327]:
```
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
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
dtype: int64
```

[328]:
```python
df.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
```

Insight: Memory usage has been reduced to 14.6 MB from 25.6 MB , reduction of 43%.

1.2 Data Exploration

Time Period if data given:

[329]:
```
df['trip_creation_time'].min(), df['trip_creation_time'].max()
```

[329]:
```
(Timestamp('2018-09-12 00:00:16.535741'),
 Timestamp('2018-10-03 23:59:42.701692'))
```

Checking Missing Source Name and Destination Name:

[330]:
```
missing_source_name = df['source_center'][df['source_name'].isna()].unique()
missing_source_name
```

[330]:
```
array(['IND342902A1B', 'IND577116AAA', 'IND282002AAD', 'IND465333A1B',
       'IND841301AAC', 'IND509103AAC', 'IND126116AAA', 'IND331022A1B',
       'IND505326AAB', 'IND852118A1B'], dtype=object)
```

[331]:
```
for i in missing_source_name:
  unique_source_name = df.loc[df['source_center']==i,'source_name'].unique()
  if pd.isna(unique_source_name):
    print(f"Source Name : {i}    Source Center : Not Found")
  else:
    print(f"Source Name : {i}    Source Center : {unique_source_name}")
```

```
Source Name : IND342902A1B    Source Center : Not Found
Source Name : IND577116AAA    Source Center : Not Found
Source Name : IND282002AAD    Source Center : Not Found
Source Name : IND465333A1B    Source Center : Not Found
Source Name : IND841301AAC    Source Center : Not Found
Source Name : IND509103AAC    Source Center : Not Found
Source Name : IND126116AAA    Source Center : Not Found
Source Name : IND331022A1B    Source Center : Not Found
```

```
Source Name : IND505326AAB    Source Center : Not Found
Source Name : IND852118A1B    Source Center : Not Found
```

[332]:
```
missing_destination_name = df['destination_center'][df['destination_name'].
 ↪isna()].unique()
missing_destination_name
```

[332]:
```
array(['IND342902A1B', 'IND577116AAA', 'IND282002AAD', 'IND465333A1B',
       'IND841301AAC', 'IND505326AAB', 'IND852118A1B', 'IND126116AAA',
       'IND509103AAC', 'IND221005A1A', 'IND250002AAC', 'IND331001A1C',
       'IND122015AAC'], dtype=object)
```

[333]:
```
for i in missing_destination_name:
  unique_destination_name = df.
 ↪loc[df['destination_center']==i,'destination_name'].unique()
  if pd.isna(unique_destination_name):
    print(f" Destination Name  : {i}    Destination Center : Not Found")
  else:
    print(f" Destination Name : {i}    Destination Center :␣
 ↪{unique_destination_name}")
```

```
 Destination Name  : IND342902A1B    Destination Center : Not Found
 Destination Name  : IND577116AAA    Destination Center : Not Found
 Destination Name  : IND282002AAD    Destination Center : Not Found
 Destination Name  : IND465333A1B    Destination Center : Not Found
 Destination Name  : IND841301AAC    Destination Center : Not Found
 Destination Name  : IND505326AAB    Destination Center : Not Found
 Destination Name  : IND852118A1B    Destination Center : Not Found
 Destination Name  : IND126116AAA    Destination Center : Not Found
 Destination Name  : IND509103AAC    Destination Center : Not Found
 Destination Name  : IND221005A1A    Destination Center : Not Found
 Destination Name  : IND250002AAC    Destination Center : Not Found
 Destination Name  : IND331001A1C    Destination Center : Not Found
 Destination Name  : IND122015AAC    Destination Center : Not Found
```

Checking ID for which source name is missing are all those Destination also missing:

[334]:
```
np.all(df.loc[df['source_name'].isna(),'source_center'].
 ↪isin(missing_destination_name))
```

[334]:
```
np.False_
```

Treating missing destination names and source names

[335]:
```
# Assign placeholder names like location_1, location_2, etc.
for i, center in enumerate(missing_destination_name, start=1):
    df.loc[df['destination_center'] == center, 'destination_name'] = \
```

```
        df.loc[df['destination_center'] == center, 'destination_name'].
↪fillna(f'location_{i}')

d2 = {}
count = len(missing_destination_name) + 1  # Continue numbering from where Part␣
↪1 left off

for center in missing_source_name:
    names = df.loc[df['destination_center'] == center, 'destination_name'].
↪dropna().unique()
    # Use existing name if found, else assign a new location
    d2[center] = names[0] if len(names) > 0 else f'location_{count}'
    if len(names) == 0:
        count += 1

for center, name in d2.items():
    print(center, name)
```

```
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
```

[336]:
```
for i in missing_source_name:
  df.loc[df['source_center']==i,'source_name'] = df.
↪loc[df['source_center']==i,'source_name'].replace(np.nan,d2[i])
```

[337]:
```
df.source_name.value_counts()
```

[337]:
```
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
                                        …
Allahabad_Mirapati_L (Uttar Pradesh)       1
Vadodara_Karelibaug_DC (Gujarat)           1
Islampure_ShbdnDPP_D (West Bengal)         1
Soro_UttarDPP_D (Orissa)                   1
Islampure_Central_DPP_2 (West Bengal)      1
```

```
Name: count, Length: 1508, dtype: int64
```

[338]:
```python
df.destination_name.value_counts()
```

[338]:
```
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
                                     …
Koppa_Sangetha_D (Karnataka)             1
Dhuri_DMComDPP_D (Punjab)                1
Sidhmukh_MnbzrDPP_D (Rajasthan)          1
Mumbai_Sanpada_CP (Maharashtra)          1
Chennai_Mylapore (Tamil Nadu)            1
Name: count, Length: 1481, dtype: int64
```

Insight: Even if we replace null values with some values they are not gonna impact on the data, so we can drop it.

[339]:
```python
# Missing count in source and destination

261+ 293
```

[339]:
```
554
```

[340]:
```python
len(df)
```

[340]:
```
144867
```

[341]:
```python
(554/144867) *100
```

[341]:
```
0.3824197367240296
```

[342]:
```python
df.isna().sum()
```

[342]:
```
data                                  0
trip_creation_time                    0
route_schedule_uuid                   0
route_type                            0
trip_uuid                             0
source_center                         0
source_name                           0
destination_center                    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
dtype: int64
```

Description of Data:

[343]:
```
df.describe()
```

[343]:
```
                  trip_creation_time                   od_start_time  \
count                         144867                          144867
mean   2018-09-22 13:34:23.659819264  2018-09-22 18:02:45.855230720
min       2018-09-12 00:00:16.535741     2018-09-12 00:00:16.535741
25%    2018-09-17 03:20:51.775845888  2018-09-17 08:05:40.886155008
50%    2018-09-22 04:24:27.932764928  2018-09-22 08:53:00.116656128
75%    2018-09-27 17:57:56.350054912  2018-09-27 22:41:50.285857024
max       2018-10-03 23:59:42.701692     2018-10-06 04:27:23.392375
std                              NaN                             NaN

                         od_end_time  start_scan_to_end_scan  \
count                         144867           144867.000000
mean   2018-09-23 10:04:31.395393024              961.262939
min       2018-09-12 00:50:10.814399               20.000000
25%    2018-09-18 01:48:06.410121984              161.000000
50%    2018-09-23 03:13:03.520212992              449.000000
75%    2018-09-28 12:49:06.054018048             1634.000000
max       2018-10-08 03:00:24.353479             7898.000000
std                              NaN             1036.997803

       actual_distance_to_destination    actual_time      osrm_time  \
count                   144867.000000  144867.000000  144867.000000
mean                       234.073380     416.927521     213.868286
min                          9.000046       9.000000       6.000000
25%                         23.355875      51.000000      27.000000
50%                         66.126572     132.000000      64.000000
75%                        286.708878     513.000000     257.000000
max                       1927.447754    4532.000000    1686.000000
std                        344.979126     598.096069     308.004333

       osrm_distance  segment_actual_time  segment_osrm_time  \
count  144867.000000        144867.000000      144867.000000
```

```
mean      284.771301          36.196110         18.507547
min         9.008200        -244.000000          0.000000
25%        29.914701          20.000000         11.000000
50%        78.525803          29.000000         17.000000
75%       343.193253          40.000000         22.000000
max      2326.199219        3051.000000       1611.000000
std       421.117462          53.566002         14.770471

       segment_osrm_distance
count          144867.000000
mean               22.829018
min                 0.000000
25%                12.070100
50%                23.513000
75%                27.813250
max              2191.403809
std                17.860197
```

[344]:
```
df.describe(include='object')
```

[344]:
```
                                      route_schedule_uuid  \
count                                              144867
unique                                               1504
top     thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f…
freq                                                 1812

                      trip_uuid source_center                  source_name  \
count                    144867        144867                       144867
unique                    14817          1508                         1508
top     trip-153759210483476123  IND000000ACB  Gurgaon_Bilaspur_HB (Haryana)
freq                        101         23347                        23347

       destination_center              destination_name
count              144867                        144867
unique               1481                          1481
top          IND000000ACB  Gurgaon_Bilaspur_HB (Haryana)
freq                15192                         15192
```

[345]:
```
df.head(10)
```

[345]:
```
       data         trip_creation_time  \
0  training 2018-09-20 02:35:36.476840
1  training 2018-09-20 02:35:36.476840
2  training 2018-09-20 02:35:36.476840
3  training 2018-09-20 02:35:36.476840
4  training 2018-09-20 02:35:36.476840
5  training 2018-09-20 02:35:36.476840
```

```
6  training 2018-09-20 02:35:36.476840
7  training 2018-09-20 02:35:36.476840
8  training 2018-09-20 02:35:36.476840
9  training 2018-09-20 02:35:36.476840

                                 route_schedule_uuid route_type  \
0  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
1  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
2  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
3  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
4  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
5  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
6  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
7  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
8  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting
9  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3…    Carting

                 trip_uuid source_center                   source_name  \
0  trip-153741093647649320  IND388121AAA     Anand_VUNagar_DC (Gujarat)
1  trip-153741093647649320  IND388121AAA     Anand_VUNagar_DC (Gujarat)
2  trip-153741093647649320  IND388121AAA     Anand_VUNagar_DC (Gujarat)
3  trip-153741093647649320  IND388121AAA     Anand_VUNagar_DC (Gujarat)
4  trip-153741093647649320  IND388121AAA     Anand_VUNagar_DC (Gujarat)
5  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
6  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
7  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
8  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
9  trip-153741093647649320  IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)

  destination_center               destination_name  \
0       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
1       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
2       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
3       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
4       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
5       IND388320AAA     Anand_Vaghasi_IP (Gujarat)
6       IND388320AAA     Anand_Vaghasi_IP (Gujarat)
7       IND388320AAA     Anand_Vaghasi_IP (Gujarat)
8       IND388320AAA     Anand_Vaghasi_IP (Gujarat)
9       IND388320AAA     Anand_Vaghasi_IP (Gujarat)

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

```
5 2018-09-20 04:47:45.236797 2018-09-20 06:36:55.627764
6 2018-09-20 04:47:45.236797 2018-09-20 06:36:55.627764
7 2018-09-20 04:47:45.236797 2018-09-20 06:36:55.627764
8 2018-09-20 04:47:45.236797 2018-09-20 06:36:55.627764
9 2018-09-20 04:47:45.236797 2018-09-20 06:36:55.627764

   start_scan_to_end_scan  actual_distance_to_destination  actual_time  \
0                    86.0                       10.435660         14.0
1                    86.0                       18.936842         24.0
2                    86.0                       27.637280         40.0
3                    86.0                       36.118027         62.0
4                    86.0                       39.386040         68.0
5                   109.0                       10.403038         15.0
6                   109.0                       18.045481         44.0
7                   109.0                       28.061895         65.0
8                   109.0                       38.939167         76.0
9                   109.0                       43.595802        102.0

   osrm_time  osrm_distance  segment_actual_time  segment_osrm_time  \
0       11.0      11.965300                 14.0               11.0
1       20.0      21.724300                 10.0                9.0
2       28.0      32.539501                 16.0                7.0
3       40.0      45.562000                 21.0               12.0
4       44.0      54.218102                  6.0                5.0
5       11.0      12.117100                 15.0               11.0
6       17.0      21.289000                 28.0                6.0
7       29.0      35.825199                 21.0               11.0
8       39.0      47.189999                 10.0               10.0
9       45.0      53.233398                 26.0                6.0

   segment_osrm_distance
0                11.9653
1                 9.7590
2                10.8152
3                13.0224
4                 3.9153
5                12.1171
6                 9.1719
7                14.5362
8                11.3648
9                 6.0434
```

Merging or rows and aggregation of fields:

[346]:
```python
grouping_1 = ['trip_uuid', 'source_center', 'destination_center']
df1 = df.groupby(grouping_1, as_index = False).agg({'data' : 'first',
                                                     'route_type' : 'first',
```

```
                                                            'trip_creation_time' :␣
↪'first',
                                                            'source_name' : 'first',
                                                            'destination_name' :␣
↪'last',
                                                            'od_start_time' :␣
↪'first',
                                                            'od_end_time' : 'first',
                                                            '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'})
```

Calculate the time taken between od_start_time and od_end_time and keep it as a feature. Drop the original columns, if required

[347]:
```
df1['od_total_time'] = df1['od_end_time'] - df1['od_start_time']
df1.drop(columns = ['od_end_time', 'od_start_time'], inplace = True)
df1['od_total_time'] = df1['od_total_time'].apply(lambda x : round(x.
 ↪total_seconds() / 60.0, 2))
df1['od_total_time'].head()
```

[347]:
```
0    1260.60
1     999.51
2      58.83
3     122.78
4     834.64
Name: od_total_time, dtype: float64
```

[348]:
```
df2 = df1.groupby(by = 'trip_uuid', as_index = False).agg({'source_center' :␣
 ↪'first',
                                                                'destination_center'␣
 ↪: 'last',
                                                                'data' : 'first',
                                                                'route_type' :␣
 ↪'first',
```

```
                                                          'trip_creation_time'␣
↪: 'first',
                                                          'source_name' :␣
↪'first',
                                                          'destination_name' :␣
↪'last',
                                                          'od_total_time' :␣
↪'sum',
                                                         ␣
↪'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'})
```

2. Build some features to prepare the data for actual analysis. Extract features from the below fields:

Source Name: Split and extract features out of destination. City-place-code (State)

[349]:
```python
def location_name_to_state(x):
    l = x.split('(')
    if len(l) == 1:
        return l[0]
    else:
        return l[1].replace(')', "")
```

[350]:
```python
def location_name_to_city(x):
    if 'location' in x:
        return 'unknown_city'
    else:
        l = x.split()[0].split('_')
        if 'CCU' in x:
            return 'Kolkata'
        elif 'MAA' in x.upper():
            return 'Chennai'
        elif ('HBR' in x.upper()) or ('BLR' in x.upper()):
            return 'Bengaluru'
```

```
        elif 'FBD' in x.upper():
            return 'Faridabad'
        elif 'BOM' in x.upper():
            return 'Mumbai'
        elif 'DEL' in x.upper():
            return 'Delhi'
        elif 'OK' in x.upper():
            return 'Delhi'
        elif 'GZB' in x.upper():
            return 'Ghaziabad'
        elif 'GGN' in x.upper():
            return 'Gurgaon'
        elif 'AMD' in x.upper():
            return 'Ahmedabad'
        elif 'CJB' in x.upper():
            return 'Coimbatore'
        elif 'HYD' in x.upper():
            return 'Hyderabad'
        return l[0]
```

[351]:
```
def location_name_to_place(x):
    if 'location' in x:
        return x
    elif 'HBR' in x:
        return 'HBR Layout PC'
    else:
        l = x.split()[0].split('_', 1)
        if len(l) == 1:
            return 'unknown_place'
        else:
            return l[1]
```

[352]:
```
df2['source_state'] = df2['source_name'].apply(location_name_to_state)
df2['source_state'].unique()
```

[352]:
```
array(['Uttar Pradesh', 'Karnataka', 'Haryana', 'Maharashtra',
       'Tamil Nadu', 'Gujarat', 'Delhi', 'Telangana', 'Rajasthan',
       'Assam', 'Madhya Pradesh', 'West Bengal', 'Andhra Pradesh',
       'Punjab', 'Chandigarh', 'Goa', 'Jharkhand', 'Pondicherry',
       'Orissa', 'Uttarakhand', 'Himachal Pradesh', 'Kerala',
       'Arunachal Pradesh', 'Bihar', 'Chhattisgarh',
       'Dadra and Nagar Haveli', 'Jammu & Kashmir', 'Mizoram', 'Nagaland',
       'location_9', 'location_3', 'location_2', 'location_14',
       'location_7'], dtype=object)
```

[353]:
```
df2['source_city'] = df2['source_name'].apply(location_name_to_city)
print('No of source cities :', df2['source_city'].nunique())
```

```
df2['source_city'].unique()[:100]
```

```
No of source cities : 690
```

[353]:
```
array(['Kanpur', 'Doddablpur', 'Gurgaon', 'Mumbai', 'Bellary', 'Chennai',
       'Bengaluru', 'Surat', 'Delhi', 'Pune', 'Faridabad', 'Shirala',
       'Hyderabad', 'Thirumalagiri', 'Gulbarga', 'Jaipur', 'Allahabad',
       'Guwahati', 'Narsinghpur', 'Shrirampur', 'Madakasira', 'Sonari',
       'Dindigul', 'Jalandhar', 'Chandigarh', 'Deoli', 'Pandharpur',
       'Kolkata', 'Bhandara', 'Kurnool', 'Bhiwandi', 'Bhatinda',
       'RoopNagar', 'Bantwal', 'Lalru', 'Kadi', 'Shahdol', 'Gangakher',
       'Durgapur', 'Vapi', 'Jamjodhpur', 'Jetpur', 'Mehsana', 'Jabalpur',
       'Junagadh', 'Gundlupet', 'Mysore', 'Goa', 'Bhopal', 'Sonipat',
       'Himmatnagar', 'Jamshedpur', 'Pondicherry', 'Anand', 'Udgir',
       'Nadiad', 'Villupuram', 'Purulia', 'Bhubaneshwar', 'Bamangola',
       'Tiruppattur', 'Kotdwara', 'Medak', 'Bangalore', 'Dhrangadhra',
       'Hospet', 'Ghumarwin', 'Agra', 'Sitapur', 'Canacona', 'Bilimora',
       'SultnBthry', 'Lucknow', 'Vellore', 'Bhuj', 'Dinhata',
       'Margherita', 'Boisar', 'Vizag', 'Tezpur', 'Koduru', 'Tirupati',
       'Pen', 'Ahmedabad', 'Faizabad', 'Gandhinagar', 'Anantapur',
       'Betul', 'Panskura', 'Rasipurm', 'Sankari', 'Jorhat', 'PNQ',
       'Srikakulam', 'Dehradun', 'Jassur', 'Sawantwadi', 'Shajapur',
       'Ludhiana', 'GreaterThane'], dtype=object)
```

[354]:
```
df2['source_place'] = df2['source_name'].apply(location_name_to_place)
df2['source_place'].unique()[:100]
```

[354]:
```
array(['Central_H_6', 'ChikaDPP_D', 'Bilaspur_HB', 'unknown_place', 'Dc',
       'Poonamallee', 'Chrompet_DPC', 'HBR Layout PC', 'Central_D_12',
       'Lajpat_IP', 'North_D_3', 'Balabhgarh_DPC', 'Central_DPP_3',
       'Shamshbd_H', 'Xroad_D', 'Nehrugnj_I', 'Central_I_7',
       'Central_H_1', 'Nangli_IP', 'North', 'KndliDPP_D', 'Central_D_9',
       'DavkharRd_D', 'Bandel_D', 'RTCStand_D', 'Central_DPP_1',
       'KGAirprt_HB', 'North_D_2', 'Central_D_1', 'DC', 'Mthurard_L',
       'Mullanpr_DC', 'Central_DPP_2', 'RajCmplx_D', 'Beliaghata_DPC',
       'RjnaiDPP_D', 'AbbasNgr_I', 'Mankoli_HB', 'DPC', 'Airport_H',
       'Hub', 'Gateway_HB', 'Tathawde_H', 'ChotiHvl_DC', 'Trmltmpl_D',
       'OnkarDPP_D', 'Mehmdpur_H', 'KaranNGR_D', 'Sohagpur_D',
       'Chrompet_L', 'Busstand_D', 'Central_I_1', 'IndEstat_I', 'Court_D',
       'Panchot_IP', 'Adhartal_IP', 'DumDum_DPC', 'Bomsndra_HB',
       'Swamylyt_D', 'Yadvgiri_IP', 'Old', 'Kundli_H', 'Central_I_3',
       'Vasanthm_I', 'Poonamallee_HB', 'VUNagar_DC', 'NlgaonRd_D',
       'Bnnrghta_L', 'Thirumtr_IP', 'GariDPP_D', 'Jogshwri_I',
       'KoilStrt_D', 'CotnGren_M', 'Nzbadrd_D', 'Dwaraka_D', 'Nelmngla_H',
       'NvygRDPP_D', 'Gndhichk_D', 'Central_D_3', 'Chowk_D', 'CharRsta_D',
       'Kollgpra_D', 'Peenya_IP', 'GndhiNgr_IP', 'Sanpada_I',
       'WrdN4DPP_D', 'Sakinaka_RP', 'CivilHPL_D', 'OstwlEmp_D',
```

```
'Gajuwaka', 'Mhbhirab_D', 'MGRoad_D', 'Balajicly_I', 'BljiMrkt_D',
'Dankuni_HB', 'Trnsport_H', 'Rakhial', 'Memnagar', 'East_I_21',
'Mithakal_D'], dtype=object)
```

Destination Name: Split and extract features out of destination. City-place-code (State)

[355]:
```
df2['destination_state'] = df2['destination_name'].apply(location_name_to_state)
df2['destination_state'].head(10)
```

[355]:
```
0    Uttar Pradesh
1        Karnataka
2          Haryana
3      Maharashtra
4        Karnataka
5       Tamil Nadu
6       Tamil Nadu
7        Karnataka
8          Gujarat
9            Delhi
Name: destination_state, dtype: object
```

[356]:
```
df2['destination_city'] = df2['destination_name'].apply(location_name_to_city)
df2['destination_city'].head()
```

[356]:
```
0        Kanpur
1    Doddablpur
2       Gurgaon
3        Mumbai
4        Sandur
Name: destination_city, dtype: object
```

[357]:
```
df2['destination_place'] = df2['destination_name'].apply(location_name_to_place)
df2['destination_place'].head()
```

[357]:
```
0    Central_H_6
1     ChikaDPP_D
2    Bilaspur_HB
3      MiraRd_IP
4     WrdN1DPP_D
Name: destination_place, dtype: object
```

Trip_creation_time: Extract features like month, year and day etc

[358]:
```
df2['trip_creation_date'] = pd.to_datetime(df2['trip_creation_time'].dt.date)
df2['trip_creation_date'].head()
```

[358]:
```
0   2018-09-12
1   2018-09-12
2   2018-09-12
3   2018-09-12
4   2018-09-12
Name: trip_creation_date, dtype: datetime64[ns]
```

[359]:
```
df2['trip_creation_day'] = df2['trip_creation_time'].dt.day
df2['trip_creation_day'] = df2['trip_creation_day'].astype('int8')
df2['trip_creation_day'].head()
```

[359]:
```
0    12
1    12
2    12
3    12
4    12
Name: trip_creation_day, dtype: int8
```

[360]:
```
df2['trip_creation_month'] = df2['trip_creation_time'].dt.month
df2['trip_creation_month'] = df2['trip_creation_month'].astype('int8')
df2['trip_creation_month'].head()
```

[360]:
```
0    9
1    9
2    9
3    9
4    9
Name: trip_creation_month, dtype: int8
```

[361]:
```
df2['trip_creation_year'] = df2['trip_creation_time'].dt.year
df2['trip_creation_year'] = df2['trip_creation_year'].astype('int16')
df2['trip_creation_year'].head()
```

[361]:
```
0    2018
1    2018
2    2018
3    2018
4    2018
Name: trip_creation_year, dtype: int16
```

[362]:
```
df2['trip_creation_week'] = df2['trip_creation_time'].dt.isocalendar().week
df2['trip_creation_week'] = df2['trip_creation_week'].astype('int8')
df2['trip_creation_week'].head()
```

[362]:
```
0    37
1    37
2    37
```

```
3    37
4    37
Name: trip_creation_week, dtype: int8
```

[363]:
```
df2['trip_creation_hour'] = df2['trip_creation_time'].dt.hour
df2['trip_creation_hour'] = df2['trip_creation_hour'].astype('int8')
df2['trip_creation_hour'].head()
```

[363]:
```
0    0
1    0
2    0
3    0
4    0
Name: trip_creation_hour, dtype: int8
```

[364]:
```
df2.describe().T
```

[364]:
```
                                  count                           mean  \
trip_creation_time                14817  2018-09-22 12:44:19.555167744
od_total_time                   14817.0                      531.69763
start_scan_to_end_scan          14817.0                     530.809998
actual_distance_to_destination  14817.0                     164.477829
actual_time                     14817.0                     357.143768
osrm_time                       14817.0                     161.384018
osrm_distance                   14817.0                     204.344711
segment_actual_time             14817.0                     353.892273
segment_osrm_time               14817.0                     180.949783
segment_osrm_distance           14817.0                     223.201157
trip_creation_date                14817  2018-09-21 23:46:58.627252736
trip_creation_day               14817.0                       18.37079
trip_creation_month             14817.0                       9.120672
trip_creation_year              14817.0                         2018.0
trip_creation_week              14817.0                      38.295944
trip_creation_hour              14817.0                      12.449821

                                                       min  \
trip_creation_time              2018-09-12 00:00:16.535741
od_total_time                                        23.46
start_scan_to_end_scan                                23.0
actual_distance_to_destination                    9.002461
actual_time                                            9.0
osrm_time                                              6.0
osrm_distance                                       9.0729
segment_actual_time                                    9.0
segment_osrm_time                                      6.0
segment_osrm_distance                               9.0729
trip_creation_date                     2018-09-12 00:00:00
```

```
trip_creation_day                                        1.0
trip_creation_month                                      9.0
trip_creation_year                                    2018.0
trip_creation_week                                      37.0
trip_creation_hour                                       0.0

                                                         25%  \
trip_creation_time             2018-09-17 02:51:25.129125888
od_total_time                                         149.93
start_scan_to_end_scan                                 149.0
actual_distance_to_destination                     22.837238
actual_time                                             67.0
osrm_time                                               29.0
osrm_distance                                      30.819201
segment_actual_time                                     66.0
segment_osrm_time                                       31.0
segment_osrm_distance                              32.654499
trip_creation_date                       2018-09-17 00:00:00
trip_creation_day                                       14.0
trip_creation_month                                      9.0
trip_creation_year                                    2018.0
trip_creation_week                                      38.0
trip_creation_hour                                       4.0

                                                         50%  \
trip_creation_time             2018-09-22 04:02:35.066945024
od_total_time                                         280.77
start_scan_to_end_scan                                 280.0
actual_distance_to_destination                     48.474072
actual_time                                            149.0
osrm_time                                               60.0
osrm_distance                                      65.618805
segment_actual_time                                    147.0
segment_osrm_time                                       65.0
segment_osrm_distance                              70.154404
trip_creation_date                       2018-09-22 00:00:00
trip_creation_day                                       19.0
trip_creation_month                                      9.0
trip_creation_year                                    2018.0
trip_creation_week                                      38.0
trip_creation_hour                                      14.0

                                                         75%  \
trip_creation_time             2018-09-27 19:37:41.898427904
od_total_time                                          638.2
start_scan_to_end_scan                                 637.0
actual_distance_to_destination                    164.583206
```

```
actual_time                                                370.0
osrm_time                                                  168.0
osrm_distance                                         208.475006
segment_actual_time                                        367.0
segment_osrm_time                                          185.0
segment_osrm_distance                                 218.802399
trip_creation_date                           2018-09-27 00:00:00
trip_creation_day                                           25.0
trip_creation_month                                          9.0
trip_creation_year                                        2018.0
trip_creation_week                                          39.0
trip_creation_hour                                          20.0

                                                        max         std
trip_creation_time              2018-10-03 23:59:42.701692          NaN
od_total_time                                      7898.55   658.868223
start_scan_to_end_scan                              7898.0   658.707031
actual_distance_to_destination                 2186.531738   305.388123
actual_time                                         6265.0    561.39502
osrm_time                                           2032.0   271.362549
osrm_distance                                  2840.081055   370.395508
segment_actual_time                                 6230.0   556.246826
segment_osrm_time                                   2564.0   314.541412
segment_osrm_distance                          3523.632324   416.628326
trip_creation_date                     2018-10-03 00:00:00          NaN
trip_creation_day                                     30.0     7.893275
trip_creation_month                                   10.0     0.325757
trip_creation_year                                  2018.0          0.0
trip_creation_week                                    40.0     0.967872
trip_creation_hour                                    23.0     7.986553
```

Q. How many trips are are being created on hourly basis?

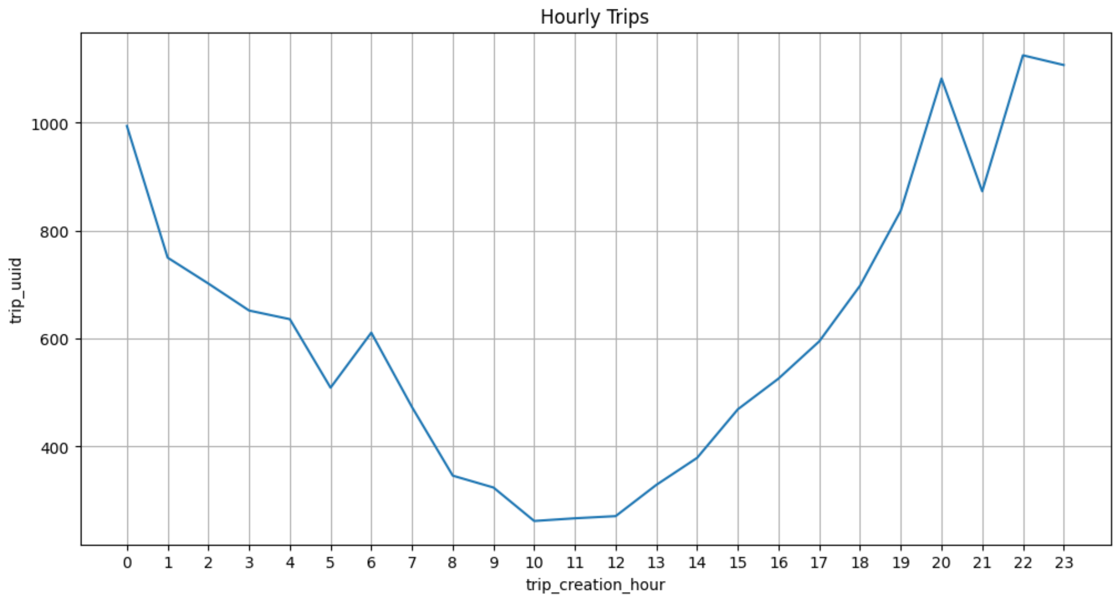
[365]:
```
hourly_trips = df2.groupby('trip_creation_hour')['trip_uuid'].count().
 ↪reset_index()
hourly_trips.head(2)
```

[365]:

	trip_creation_hour	trip_uuid
0	0	994
1	1	750

[366]:
```
plt.figure(figsize = (12, 6))
sns.lineplot(data=␣
 ↪hourly_trips,x=hourly_trips['trip_creation_hour'],y=hourly_trips['trip_uuid'])
plt.title('Hourly Trips')
plt.xticks(np.arange(0,24))
plt.grid('both')
```

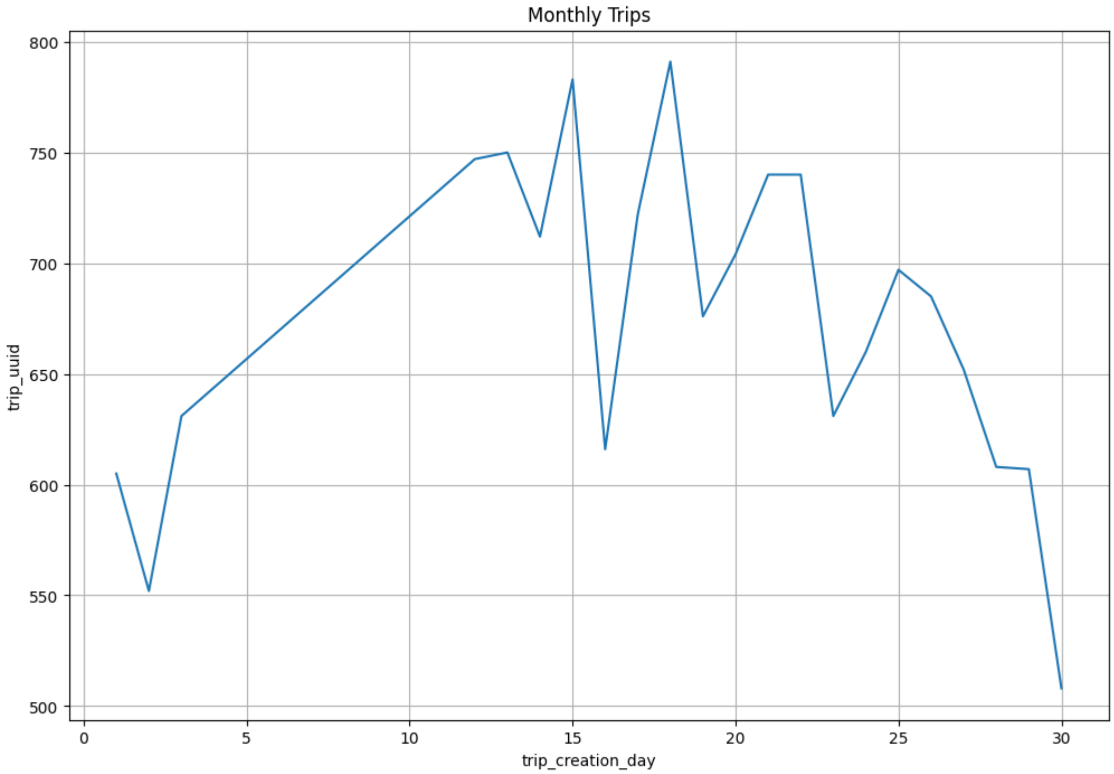
```
plt.show()
```



Insight: Number of trips are getting started around 10A.M to night and again starts decreasing.

Q. Let's find out how many trips are created for different days of month.

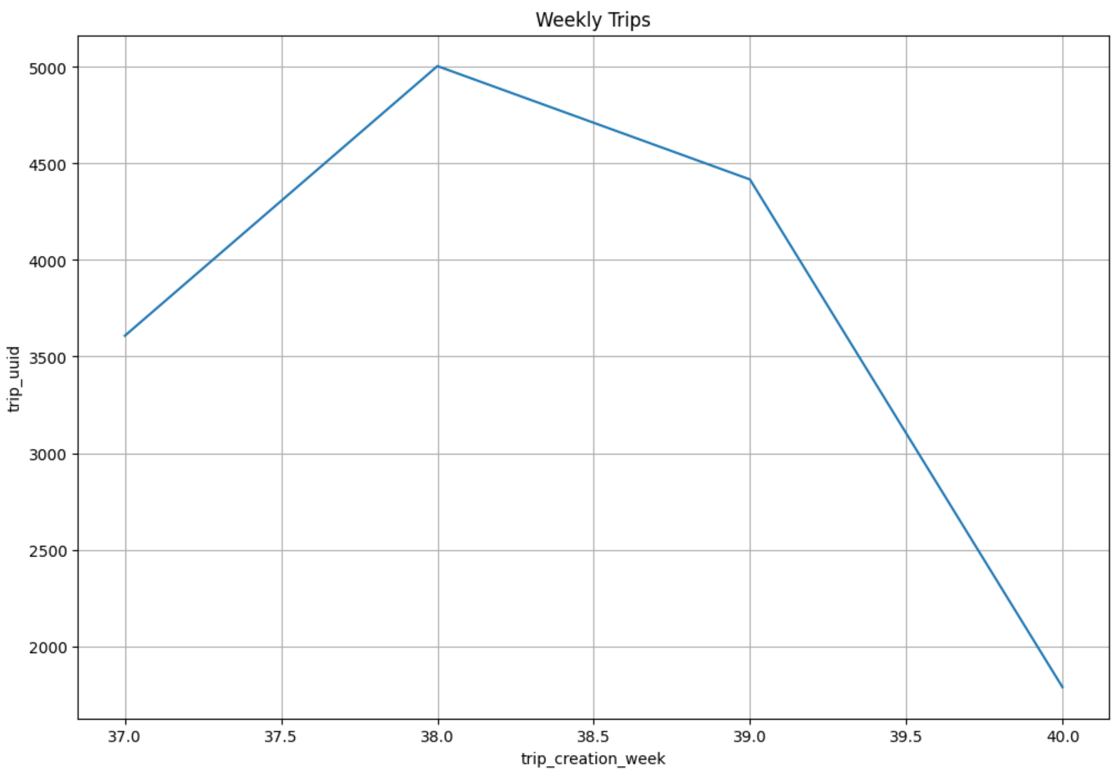
[367]:
```
monthly_trips = df2.groupby('trip_creation_day')['trip_uuid'].count().
↪reset_index()

plt.figure(figsize = (12,8))
sns.lineplot(data= monthly_trips , x=monthly_trips['trip_creation_day'],␣
↪y=monthly_trips['trip_uuid'])
plt.title('Monthly Trips')
plt.grid('both')
plt.show()
```



Insight: Most of the trips are created at mid of the month,there is chance that customer make more orders during mid of the month.

Q. Lets find out the how many trips created for different weeks

[368]:
```
weekly_trips = df2.groupby('trip_creation_week')['trip_uuid'].count().
 ↪reset_index()

plt.figure(figsize = (12,8))
sns.lineplot(data= weekly_trips , x=weekly_trips['trip_creation_week'],␣
 ↪y=weekly_trips['trip_uuid'])
plt.title('Weekly Trips')
plt.grid('both')
plt.show()
```



Insight: In 38th week most of orders are being created.

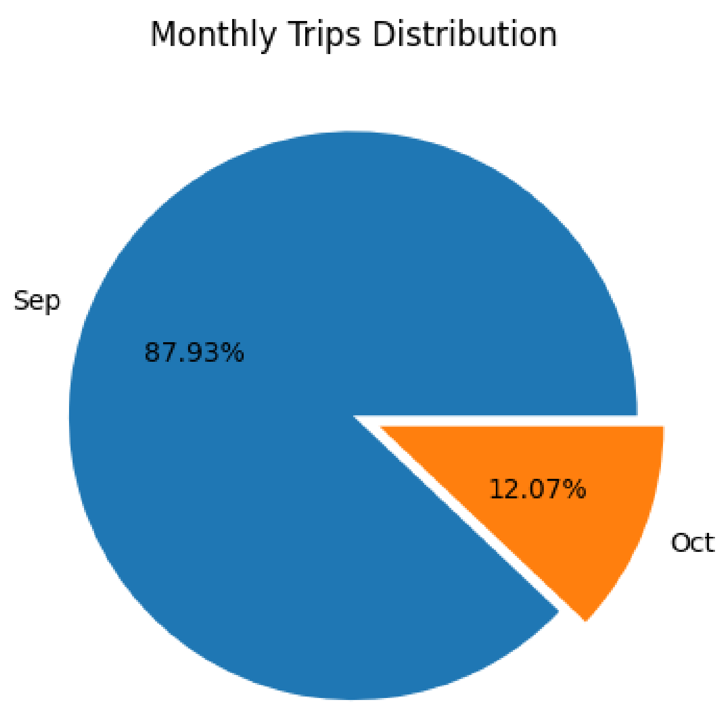
Q. How many trips are created over given two months time period

[369]:
```
monthly_trips = df2.groupby('trip_creation_month')['trip_uuid'].count().
  ↪reset_index()
monthly_trips['Percentage'] = round(monthly_trips['trip_uuid']/df2.
  ↪shape[0]*100,2)
monthly_trips
```

[369]:

	trip_creation_month	trip_uuid	Percentage
0	9	13029	87.93
1	10	1788	12.07

[370]:
```
plt.pie(x = monthly_trips['trip_uuid'],
        labels = ['Sep', 'Oct'],
        explode = [0, 0.1],
       autopct = '%.2f%%')
plt.title("Monthly Trips Distribution")
plt.show()
```



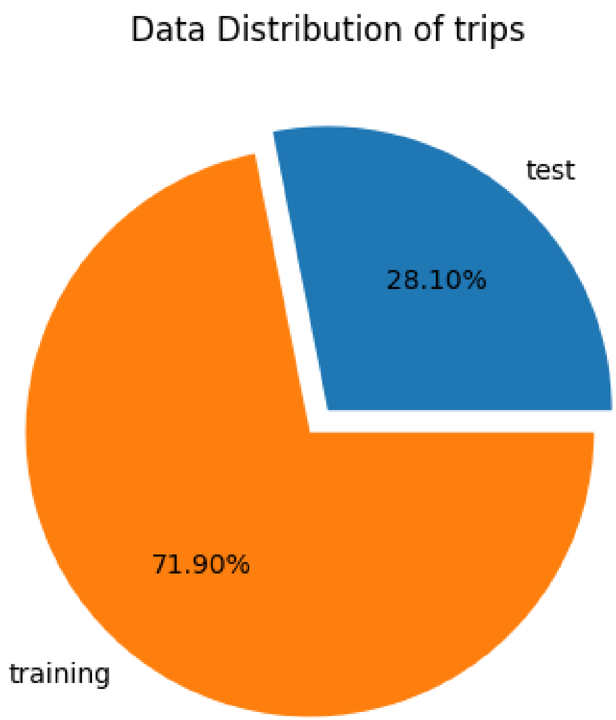
Q. Trip distribution for data

[371]:
```
df2_data = df2.groupby('data')['trip_uuid'].count().reset_index()
df2_data['perc'] = np.round(df2_data['trip_uuid'] * 100/ df2_data['trip_uuid'].
↪sum(), 2)
df2_data.head()
```

[371]:

	data	trip_uuid	perc
0	test	4163	28.1
1	training	10654	71.9

[372]:
```
plt.pie(x = df2_data['trip_uuid'], labels=['test','training'], autopct='%.
↪2f%%', explode=[0,0.1] )
plt.title("Data Distribution of trips")
plt.show()
```



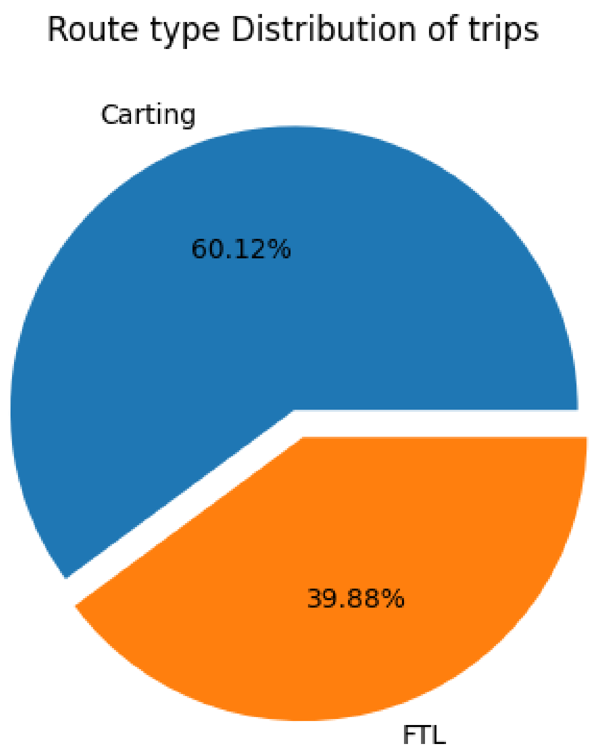
Q.Distribution of route types for the orders

[373]:
```
df_route = df2.groupby('route_type')['trip_uuid'].count().reset_index()
df_route['perc'] = np.round(df_route['trip_uuid'] * 100/ df_route['trip_uuid'].
    ↪sum(), 2)
df_route.head()
```

[373]:

	route_type	trip_uuid	perc
0	Carting	8908	60.12
1	FTL	5909	39.88

[374]:
```
plt.pie(x = df_route['trip_uuid'], labels=['Carting','FTL'], autopct='%.2f%%',␣
    ↪explode=[0,0.1] )
plt.title("Route type Distribution of trips")
plt.show()
```



Q.Distribution of number of trips created form different states.

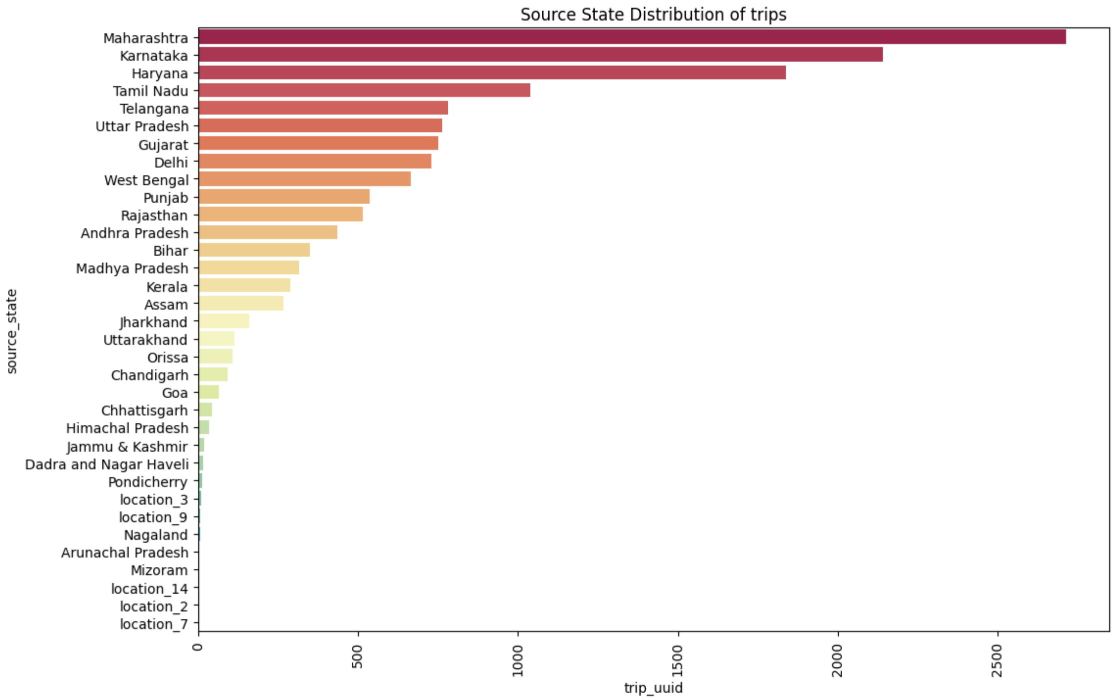
[375]:
```
df_source_state = df2.groupby(by = 'source_state')['trip_uuid'].count().
 ↪to_frame().reset_index()
df_source_state['perc'] = np.round(df_source_state['trip_uuid'] * 100/␣
 ↪df_source_state['trip_uuid'].sum(), 2)
df_source_state = df_source_state.sort_values(by = 'trip_uuid', ascending =␣
 ↪False)
df_source_state.head()
```

[375]:

	source_state	trip_uuid	perc
17	Maharashtra	2714	18.32
14	Karnataka	2143	14.46
10	Haryana	1838	12.40
24	Tamil Nadu	1039	7.01
25	Telangana	781	5.27

[376]:
```
plt.figure(figsize=(12,8))
sns.barplot(data=df_source_state ,␣
 ↪y=df_source_state['source_state'],x=df_source_state['trip_uuid'],palette="Spectral")
plt.title("Source State Distribution of trips")
plt.xticks(rotation=90)
```

```
plt.show()
```



Insights:

1. Sellers have strong base in Maharashtra, Karnataka, Haryana and Tamilnadu.

Q. Lets check which cities have high trips

[377]:
```
citywise_trips = df2.groupby('source_city')['trip_uuid'].count().reset_index()
citywise_trips['Percenatage'] = round(citywise_trips['trip_uuid']/df2.
↪shape[0]*100,2)
citywise_trips = citywise_trips.sort_values(by='Percenatage', ascending=False)[:
↪20]
citywise_trips
```

[377]:

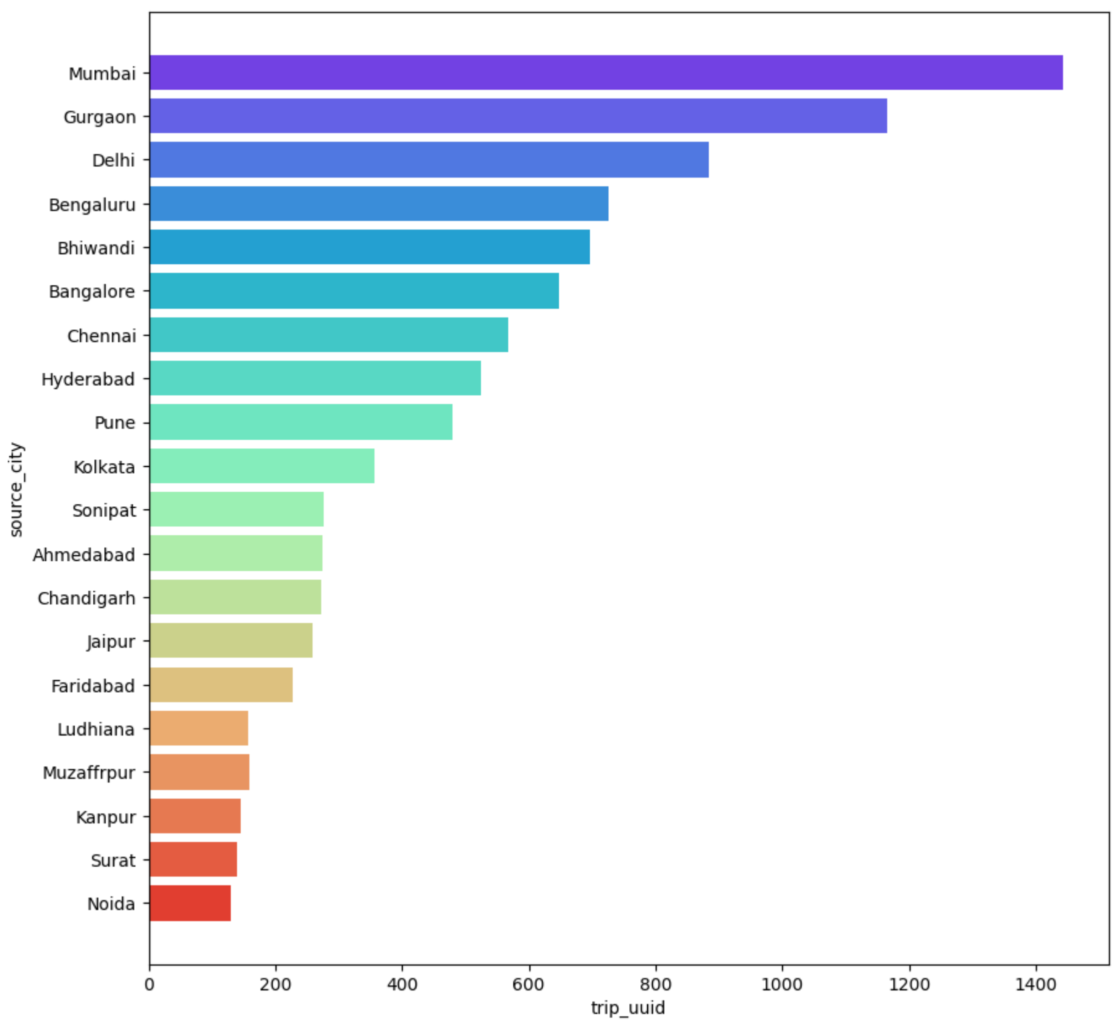
	source_city	trip_uuid	Percenatage
439	Mumbai	1442	9.73
237	Gurgaon	1165	7.86
169	Delhi	883	5.96
79	Bengaluru	726	4.90
100	Bhiwandi	697	4.70
58	Bangalore	648	4.37
136	Chennai	568	3.83
264	Hyderabad	524	3.54
516	Pune	480	3.24

```
357      Kolkata         356         2.40
610      Sonipat         276         1.86
2      Ahmedabad         274         1.85
133   Chandigarh         273         1.84
270       Jaipur         259         1.75
201    Faridabad         227         1.53
382     Ludhiana         158         1.07
447   Muzaffrpur         159         1.07
320       Kanpur         145         0.98
621        Surat         140         0.94
473        Noida         129         0.87
```

[378]:

```python
plt.figure(figsize = (10, 10))
sns.barplot(data = citywise_trips, x = citywise_trips['trip_uuid'], y =␣
↪citywise_trips['source_city'],palette='rainbow')
plt.plot()
```

[378]: []



Insights: It can be seen in the above plot that maximum trips originated from Mumbai city followed by Gurgaon Delhi, Bengaluru and Bhiwandi. That means that the seller base is strong in these cities.

Q. Distribution of number of trips which ended in different states

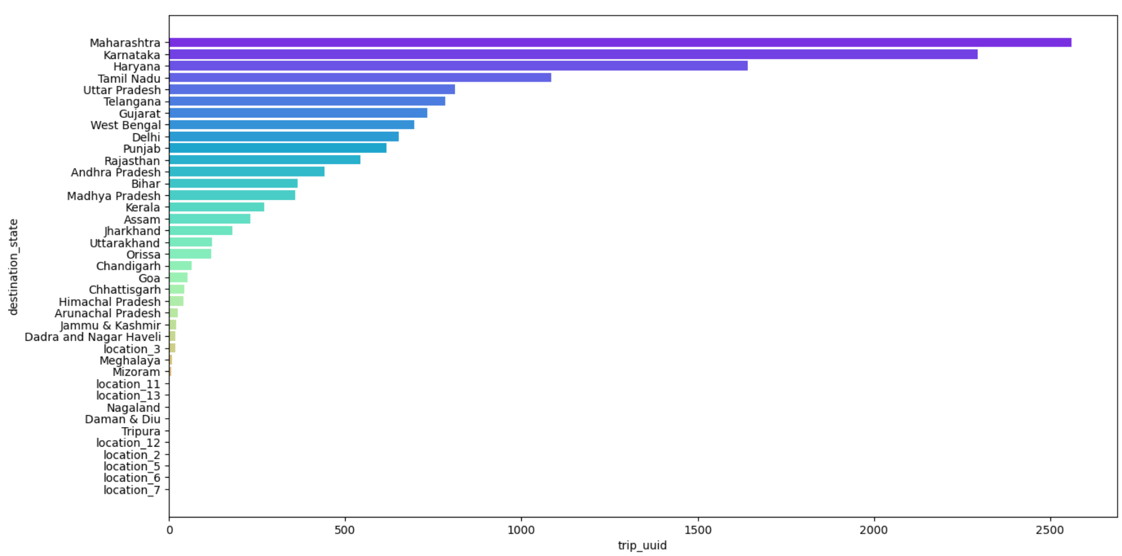
[379]:
```
df_destination_state = df2.groupby(by = 'destination_state')['trip_uuid'].
↪count().to_frame().reset_index()
df_destination_state['perc'] = np.round(df_destination_state['trip_uuid'] * 100/
↪ df_destination_state['trip_uuid'].sum(), 2)
df_destination_state = df_destination_state.sort_values(by = 'trip_uuid',␣
↪ascending = False)
df_destination_state.head()
```

[379]:

	destination_state	trip_uuid	perc
18	Maharashtra	2561	17.28
15	Karnataka	2294	15.48
11	Haryana	1643	11.09
25	Tamil Nadu	1084	7.32
28	Uttar Pradesh	811	5.47

[380]:
```
plt.figure(figsize = (15, 8))
sns.barplot(data = df_destination_state, x = df_destination_state['trip_uuid'],␣
↪y = df_destination_state['destination_state'],palette='rainbow')
plt.plot()
```

[380]: []



Insights: It can be seen in the above plot that maximum trips ended in Maharashtra state followed by Karnataka, Haryana, Tamil Nadu and Uttar Pradesh. That means that the number of orders placed in these states is significantly high in these states.

Q. top 30 cities based on the number of trips ended in different cities

[381]:
```
df_destination_city = df2.groupby(by = 'destination_city')['trip_uuid'].count().
    ↪to_frame().reset_index()
df_destination_city['perc'] = np.round(df_destination_city['trip_uuid'] * 100/␣
    ↪df_destination_city['trip_uuid'].sum(), 2)
df_destination_city = df_destination_city.sort_values(by = 'trip_uuid',␣
    ↪ascending = False)[:30]
df_destination_city
```

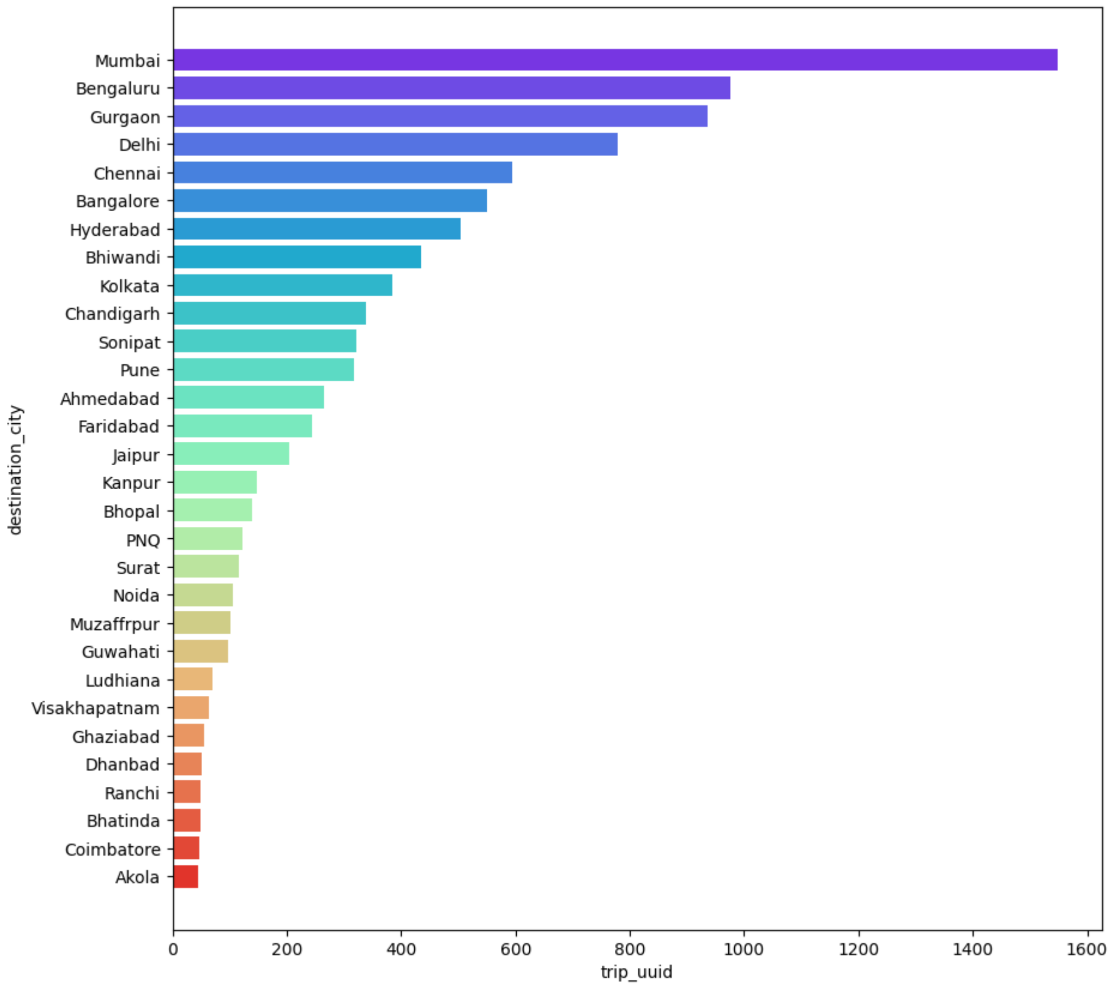
[381]:

	destination_city	trip_uuid	perc
515	Mumbai	1548	10.45
96	Bengaluru	975	6.58
282	Gurgaon	936	6.32
200	Delhi	778	5.25
163	Chennai	595	4.02
72	Bangalore	551	3.72
308	Hyderabad	503	3.39
115	Bhiwandi	434	2.93
418	Kolkata	384	2.59
158	Chandigarh	339	2.29
724	Sonipat	322	2.17
612	Pune	317	2.14
4	Ahmedabad	265	1.79
242	Faridabad	244	1.65
318	Jaipur	205	1.38
371	Kanpur	148	1.00
117	Bhopal	139	0.94
559	PNQ	122	0.82
739	Surat	117	0.79
552	Noida	106	0.72
521	Muzaffrpur	102	0.69
284	Guwahati	98	0.66
448	Ludhiana	70	0.47
797	Visakhapatnam	64	0.43
259	Ghaziabad	56	0.38
208	Dhanbad	50	0.34
639	Ranchi	49	0.33
110	Bhatinda	48	0.32
183	Coimbatore	47	0.32
9	Akola	45	0.30

[382]:
```
plt.figure(figsize = (10, 10))
```

```
sns.barplot(data = df_destination_city, x = df_destination_city['trip_uuid'], y␣
↪= df_destination_city['destination_city'],palette='rainbow')
plt.plot()
```

[382]: []



Insight: It can be seen in the above plot that maximum trips ended in Mumbai city followed by Bengaluru, Gurgaon, Delhi and Chennai. That means that the number of orders placed in these cities is significantly high.

[383]:
```
numerical_columns = ['od_total_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']
```

[384]:
```
df_corr = df2[numerical_columns].corr()
df_corr
```

[384]:

	od_total_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
od_total_time	1.000000	0.999999	0.918222	0.961094	0.926516	0.924219	0.961119	0.918490	0.919199
start_scan_to_end_scan	0.999999	1.000000	0.918308	0.961147	0.926571	0.924299	0.961171	0.918561	0.919291
actual_distance_to_destination	0.918222	0.918308	1.000000	0.953757	0.993561	0.997264	0.952821	0.987538	0.993061
actual_time	0.961094	0.961147	0.953757	1.000000	0.958593	0.959214	0.999989	0.953872	0.956967
osrm_time	0.926516	0.926571	0.993561	0.958593	1.000000	0.997580	0.957765	0.993259	0.991608
osrm_distance	0.924219	0.924299	0.997264	0.959214	0.997580	1.000000	0.958353	0.991798	0.994710
segment_actual_time	0.961119	0.961171	0.952821	0.999989	0.957765	0.958353	1.000000	0.953039	0.956106
segment_osrm_time	0.918490	0.918561	0.987538	0.953872	0.993259	0.991798	0.953039	1.000000	0.996092
segment_osrm_distance	0.919199	0.919291	0.993061	0.956967	0.991608	0.994710	0.956106	0.996092	1.000000

Insight: Very High Correlation (> 0.9) exists between columns all the numerical columns specified above

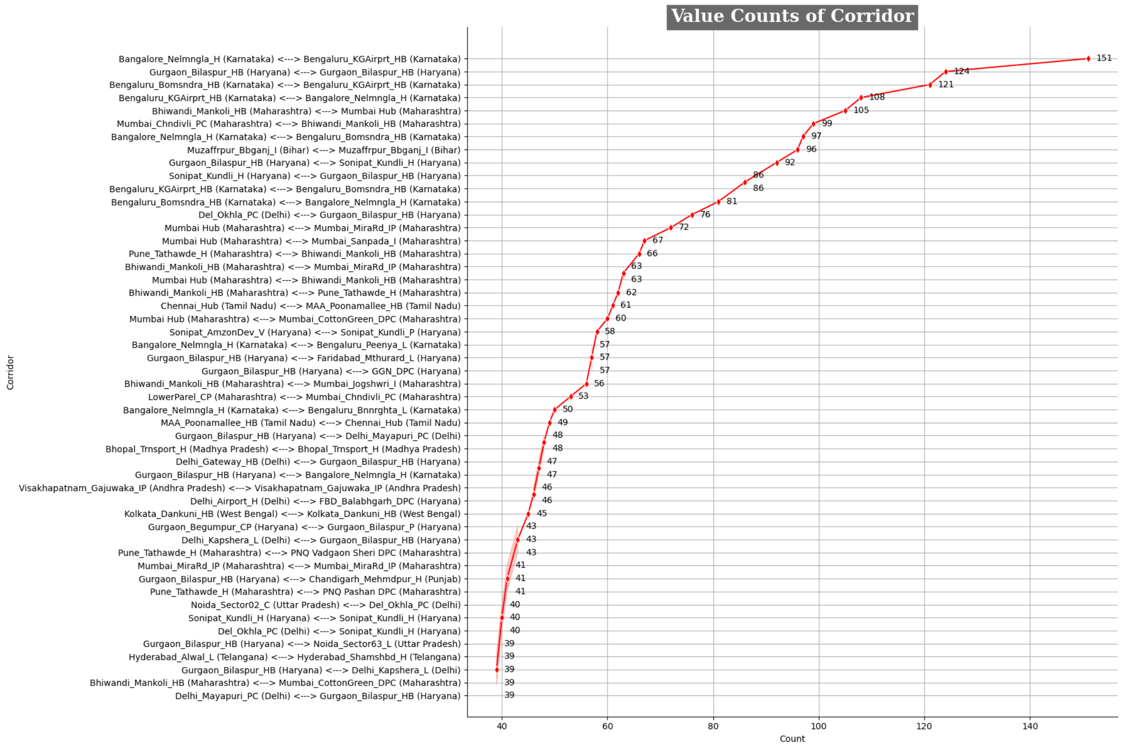
Busiest corridor, avg distance between them, avg time taken

[385]:
```
df2['corridor'] = df2['source_name'] +' <---> '+ df2['destination_name']
df2['corridor'].value_counts()
```

[385]:
```
corridor
Bangalore_Nelmngla_H (Karnataka) <---> Bengaluru_KGAirprt_HB (Karnataka)
151
Gurgaon_Bilaspur_HB (Haryana) <---> Gurgaon_Bilaspur_HB (Haryana)
124
Bengaluru_Bomsndra_HB (Karnataka) <---> Bengaluru_KGAirprt_HB (Karnataka)
121
Bengaluru_KGAirprt_HB (Karnataka) <---> Bangalore_Nelmngla_H (Karnataka)
108
Bhiwandi_Mankoli_HB (Maharashtra) <---> Mumbai Hub (Maharashtra)
105
  …
Karad_Mundhe_D (Maharashtra) <---> Kolhapur_Central_H_2 (Maharashtra)
1
Bhiwani_DC (Haryana) <---> Loharu_BstndDPP_D (Haryana)
1
Shadnagar_Central_D_1 (Telangana) <---> Shadnagar_Central_D_1 (Telangana)
1
Mainpuri_Agraroad_I (Uttar Pradesh) <---> Farrukhbad_Pnchlght_D (Uttar Pradesh)
1
Moga_DPC (Punjab) <---> Ludhiana_MilrGanj_HB (Punjab)
1
Name: count, Length: 2179, dtype: int64
```

[386]:
```
corridor_counts = df2['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=
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:

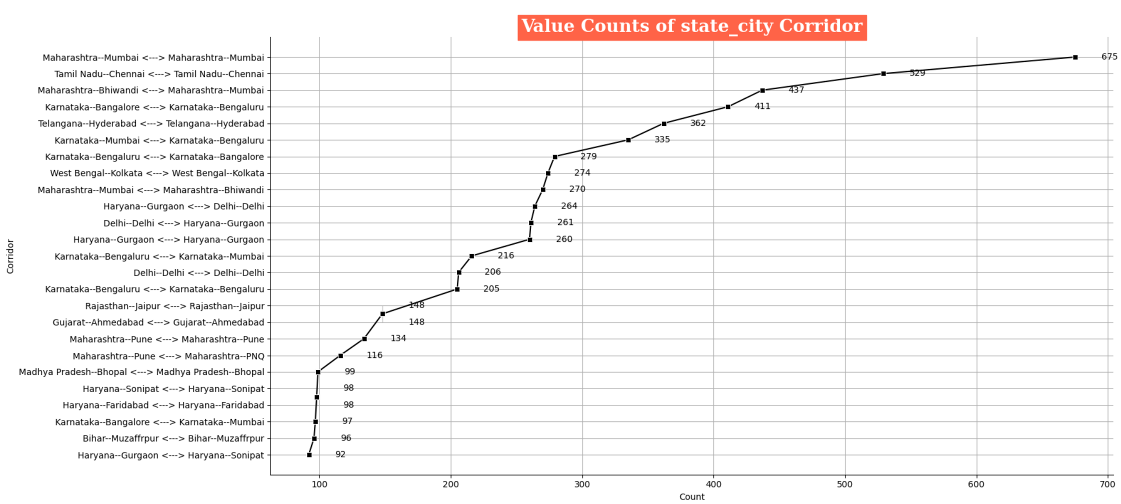
1. The route between Bangalore_Nelamangala_H to Bengaluru_KGAirport_HB,Bengaluru_Bomsndra_HB sees the highest package volume, with 151 and 127 packages sent respectively.
2. Bengaluru_Bommasandra_HB to Bengaluru_KGAirport_HB is also popular, with 121 packages sent.
3. Bengaluru_KGAirport_HB to Bangalore_Nelamangala_H has moderate activity, with 108 packages sent

[387]:
```
df2['state_corridor'] = df2['source_state']+'--'+df2['source_city'] +' <---> '+␣
 ↪df2['destination_state']+'--'+df2['destination_city']
df2['state_corridor'].value_counts()
```

[387]:
```
state_corridor
Maharashtra--Mumbai <---> Maharashtra--Mumbai                  675
Tamil Nadu--Chennai <---> Tamil Nadu--Chennai                  529
Maharashtra--Bhiwandi <---> Maharashtra--Mumbai                437
Karnataka--Bangalore <---> Karnataka--Bengaluru                411
```

```
Telangana--Hyderabad <---> Telangana--Hyderabad             362
                                                           …
Tamil Nadu--Madurai <---> Tamil Nadu--Madurai                 1
Telangana--Bengaluru <---> Telangana--Manthani                1
Rajasthan--Sikar <---> Rajasthan--Khetri                      1
Uttar Pradesh--Gorakhpur <---> Uttar Pradesh--Anandnagar      1
West Bengal--Kolkata <---> West Bengal--Baruipur              1
Name: count, Length: 1686, dtype: int64
```

[388]:
```
state_corridor_counts = df2['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='
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()
```

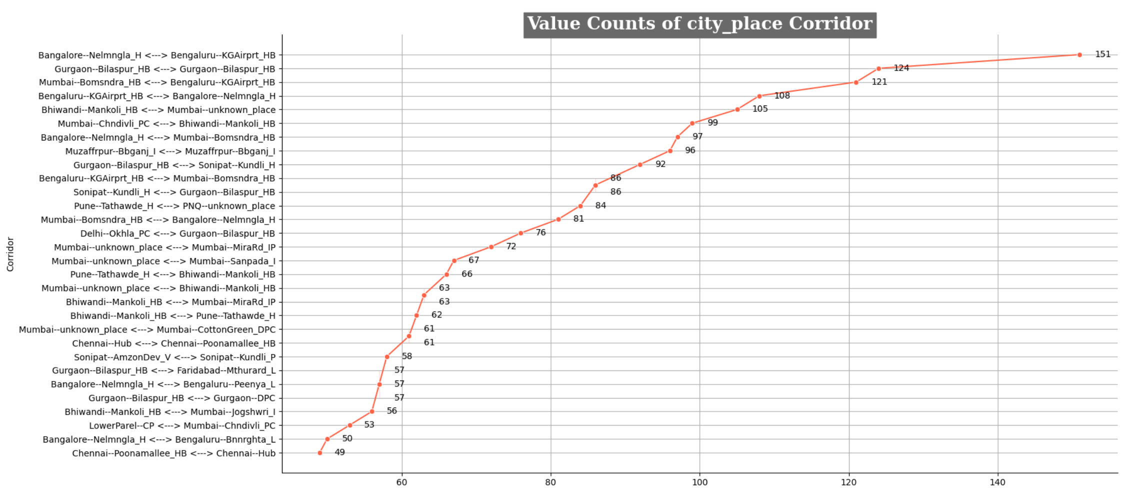


[389]:
```
df2['city_corridor'] = df2['source_city']+'--'+df2['source_place'] +' <---> '+␣
 ↪df2['destination_city']+'--'+df2['destination_place']
display(df2['city_corridor'].value_counts())
```

```
city_corridor
```

```
Bangalore--Nelmngla_H <---> Bengaluru--KGAirprt_HB       151
Gurgaon--Bilaspur_HB <---> Gurgaon--Bilaspur_HB          124
Mumbai--Bomsndra_HB <---> Bengaluru--KGAirprt_HB         121
Bengaluru--KGAirprt_HB <---> Bangalore--Nelmngla_H       108
Bhiwandi--Mankoli_HB <---> Mumbai--unknown_place         105
                                                        ...
Chennai--Porur_DPC <---> Chennai--Vepmpttu_DC              1
Bhadrachalam--ITDARd_D <---> Sathupally--VidyaNGR_D        1
Deoghar--Barmasia_D <---> Madhupur--Sitarmrd_D             1
Delhi--Patparganj_DPC <---> Delhi--Shahdara                1
Luxettipet--ShivaDPP_D <---> unknown_city--location_6      1
Name: count, Length: 2173, dtype: int64
```

[390]:
```python
city_corridor_counts = df2['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=
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:

1. Maharashtra, Karnataka, Haryana, and Tamil Nadu serve as key starting and ending locations for delivery services.
2. Mumbai, Gurgaon, Delhi, and Bengaluru are major metropolitan centers from where many deliveries originate.
3. A large proportion of nationwide deliveries are destined for Mumbai, Bengaluru, Gurgaon, and Delhi.

1.3 Outlier Detection & Treatment

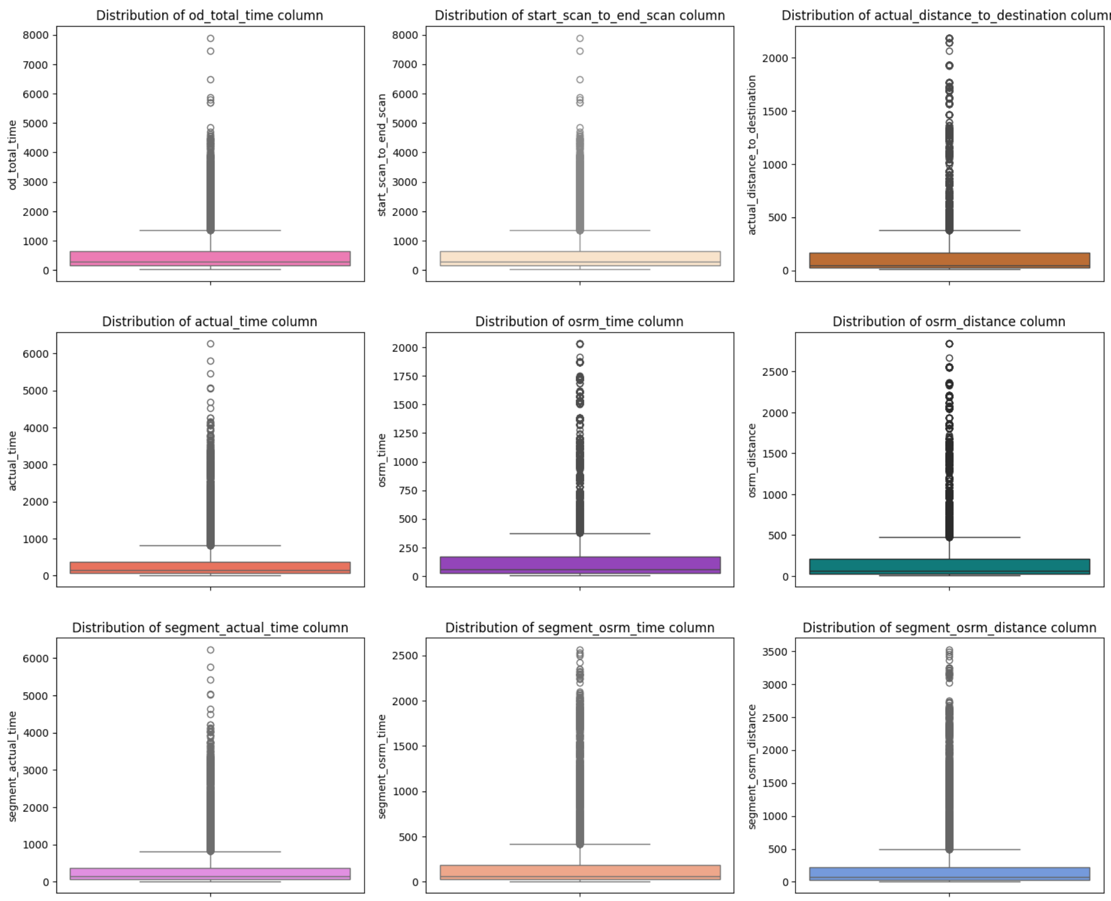
Finding outliers in the numerical variables, and check it using visual analysis

[391]:
```
num_cols = ['od_total_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']
df2[num_cols].describe().T
```

[391]:
```
                                  count        mean         std        min  \
od_total_time                   14817.0  531.697630  658.868223  23.460000
start_scan_to_end_scan          14817.0  530.809998  658.707031  23.000000
actual_distance_to_destination  14817.0  164.477829  305.388123   9.002461
actual_time                     14817.0  357.143768  561.395020   9.000000
osrm_time                       14817.0  161.384018  271.362549   6.000000
osrm_distance                   14817.0  204.344711  370.395508   9.072900
segment_actual_time             14817.0  353.892273  556.246826   9.000000
segment_osrm_time               14817.0  180.949783  314.541412   6.000000
segment_osrm_distance           14817.0  223.201157  416.628326   9.072900

                                       25%         50%         75%  \
od_total_time                   149.930000  280.770000  638.200000
start_scan_to_end_scan          149.000000  280.000000  637.000000
actual_distance_to_destination   22.837238   48.474072  164.583206
actual_time                      67.000000  149.000000  370.000000
osrm_time                        29.000000   60.000000  168.000000
osrm_distance                    30.819201   65.618805  208.475006
segment_actual_time              66.000000  147.000000  367.000000
segment_osrm_time                31.000000   65.000000  185.000000
segment_osrm_distance            32.654499   70.154404  218.802399

                                        max
od_total_time                   7898.550000
start_scan_to_end_scan          7898.000000
actual_distance_to_destination  2186.531738
actual_time                     6265.000000
osrm_time                       2032.000000
osrm_distance                   2840.081055
segment_actual_time             6230.000000
```

```
segment_osrm_time                2564.000000
segment_osrm_distance            3523.632324
```

[392]:
```python
plt.figure(figsize = (18, 15))
for i in range(len(num_cols)):
    plt.subplot(3, 3, i + 1)
    clr = np.random.choice(list(mpl.colors.cnames))
    sns.boxplot(df2[num_cols[i]], color = clr)
    plt.title(f"Distribution of {num_cols[i]} column")
    plt.plot()
```



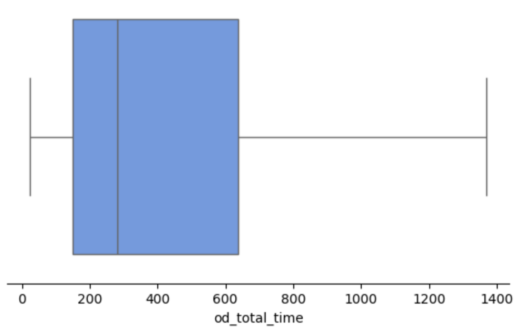
[393]:
```python
for i, col in enumerate(num_cols):

  data = df2[col]
  display(data.to_frame())


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

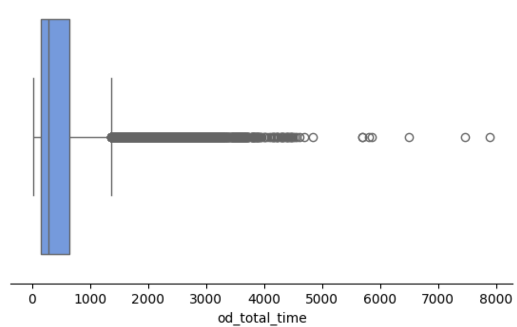
```
IQR = Q3 - Q1

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=clr)
sns.despine(left=True)
plt.yticks([])
plt.title(f'Boxplot of clipped {col}', fontfamily='serif', fontweight='bold',␣
↪fontsize=12, 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=clr)
sns.despine(left=True)
plt.yticks([])
plt.title(f'Boxplot of filtered {col}', fontfamily='serif', fontweight='bold',␣
↪fontsize=12, color='w')

plt.show()
```

```
       od_total_time
0            2260.11
1             181.61
2            3934.36
3             100.49
4             718.34
…                …
14812         258.03
14813          60.59
14814         422.12
14815         348.52
14816         354.40

[14817 rows x 1 columns]
```

```
Clipped data of od_total_time

       od_total_time
0           1370.605
1            181.610
2           1370.605
3            100.490
4            718.340
…              …
14812        258.030
14813         60.590
14814        422.120
14815        348.520
14816        354.400

[14817 rows x 1 columns]
```

```
Filtered data of od_total_time

       od_total_time
0            2260.11
1             181.61
2            3934.36
3             100.49
4             718.34
…              …
14812         258.03
14813          60.59
14814         422.12
14815         348.52
14816         354.40

[14817 rows x 1 columns]
```





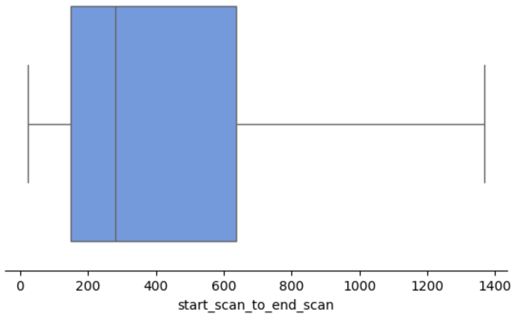
```
       start_scan_to_end_scan
0                    2259.0
1                     180.0
2                    3933.0
3                     100.0
4                     717.0
…                    …
14812                 257.0
14813                  60.0
14814                 421.0
14815                 347.0
14816                 353.0

[14817 rows x 1 columns]
```

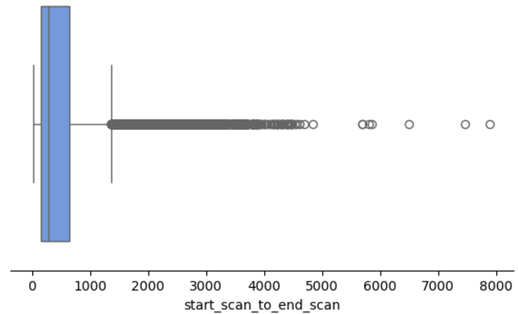
Clipped data of start_scan_to_end_scan

```
       start_scan_to_end_scan
0                    1369.0
1                     180.0
2                    1369.0
3                     100.0
4                     717.0
…                    …
14812                 257.0
14813                  60.0
14814                 421.0
14815                 347.0
14816                 353.0

[14817 rows x 1 columns]
```

Filtered data of start_scan_to_end_scan

```
       start_scan_to_end_scan
0                    2259.0
1                     180.0
2                    3933.0
3                     100.0
4                     717.0
…                    …
14812                 257.0
14813                  60.0
14814                 421.0
14815                 347.0
14816                 353.0

[14817 rows x 1 columns]
```





	actual_distance_to_destination
0	824.732849
1	73.186905
2	1927.404297
3	17.175274
4	127.448502
…	…
14812	57.762333
14813	15.513784
14814	38.684837
14815	134.723831
14816	66.081528

[14817 rows x 1 columns]

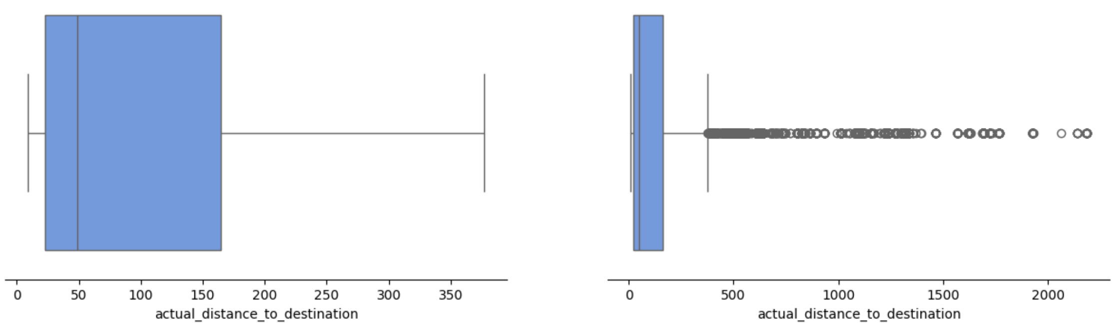
Clipped data of actual_distance_to_destination

	actual_distance_to_destination
0	377.202148
1	73.186905
2	377.202148
3	17.175274
4	127.448502
…	…
14812	57.762333
14813	15.513784
14814	38.684837
14815	134.723831
14816	66.081528

[14817 rows x 1 columns]

Filtered data of actual_distance_to_destination

```
       actual_distance_to_destination
0                          824.732849
1                           73.186905
2                         1927.404297
3                           17.175274
4                          127.448502
…                                   …
14812                       57.762333
14813                       15.513784
14814                       38.684837
14815                      134.723831
14816                       66.081528

[14817 rows x 1 columns]
```

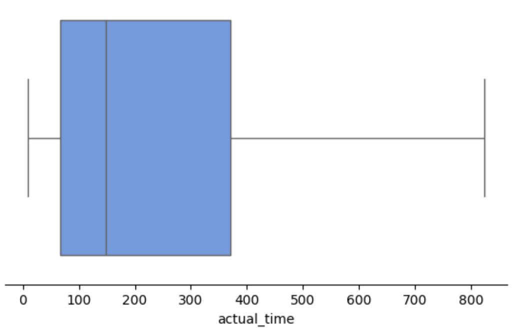


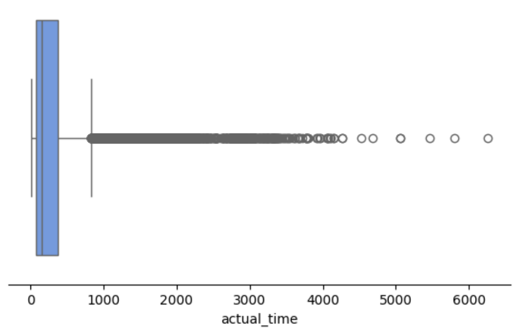

```
       actual_time
0           1562.0
1            143.0
2           3347.0
3             59.0
4            341.0
…              …
14812         83.0
14813         21.0
14814        282.0
14815        264.0
14816        275.0

[14817 rows x 1 columns]
```

Clipped data of actual_time

```
       actual_time
0            824.5
```

```
1            143.0
2            824.5
3             59.0
4            341.0
…            …
14812         83.0
14813         21.0
14814        282.0
14815        264.0
14816        275.0

[14817 rows x 1 columns]


Filtered data of actual_time

       actual_time
0           1562.0
1            143.0
2           3347.0
3             59.0
4            341.0
…            …
14812         83.0
14813         21.0
14814        282.0
14815        264.0
14816        275.0

[14817 rows x 1 columns]
```






```
       osrm_time
0          717.0
1           68.0
```

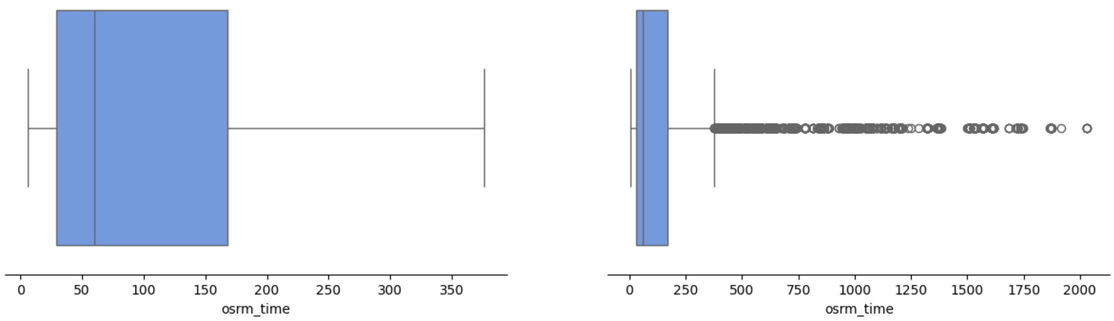
```
2         1740.0
3           15.0
4          117.0
…          …
14812       62.0
14813       12.0
14814       48.0
14815      179.0
14816       68.0

[14817 rows x 1 columns]
```

```
Clipped data of osrm_time
```

```
       osrm_time
0          376.5
1           68.0
2          376.5
3           15.0
4          117.0
…          …
14812       62.0
14813       12.0
14814       48.0
14815      179.0
14816       68.0

[14817 rows x 1 columns]
```

```
Filtered data of osrm_time
```

```
       osrm_time
0          717.0
1           68.0
2         1740.0
3           15.0
4          117.0
…          …
14812       62.0
14813       12.0
14814       48.0
14815      179.0
14816       68.0

[14817 rows x 1 columns]
```




```
       osrm_distance
0         991.352295
1          85.111000
2        2354.066650
3          19.680000
4         146.791794
…                …
14812      73.462997
14813      16.088200
14814      58.903702
14815     171.110306
14816      80.578705

[14817 rows x 1 columns]
```

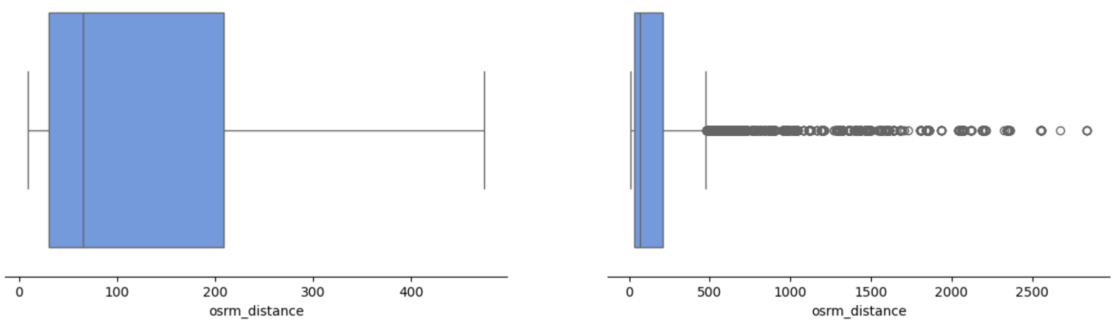
Clipped data of osrm_distance

```
       osrm_distance
0         474.958710
1          85.111000
2         474.958710
3          19.680000
4         146.791794
…                …
14812      73.462997
14813      16.088200
14814      58.903702
14815     171.110306
14816      80.578705

[14817 rows x 1 columns]
```

Filtered data of osrm_distance

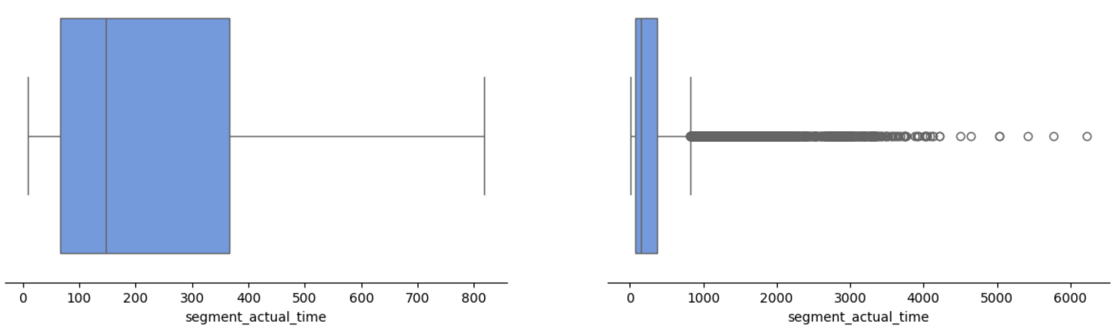
```
       osrm_distance
```

```
0          991.352295
1           85.111000
2         2354.066650
3           19.680000
4          146.791794
…                 …
14812       73.462997
14813       16.088200
14814       58.903702
14815      171.110306
14816       80.578705

[14817 rows x 1 columns]
```




```
       segment_actual_time
0                   1548.0
1                    141.0
2                   3308.0
3                     59.0
4                    340.0
…                    …
14812                 82.0
14813                 21.0
14814                281.0
14815                258.0
14816                274.0

[14817 rows x 1 columns]

Clipped data of segment_actual_time

       segment_actual_time
0                    818.5
1                    141.0
```

```
2                     818.5
3                      59.0
4                     340.0
…                     …
14812                  82.0
14813                  21.0
14814                 281.0
14815                 258.0
14816                 274.0

[14817 rows x 1 columns]


Filtered data of segment_actual_time

       segment_actual_time
0                   1548.0
1                    141.0
2                   3308.0
3                     59.0
4                    340.0
…                    …
14812                 82.0
14813                 21.0
14814                281.0
14815                258.0
14816                274.0

[14817 rows x 1 columns]
```




```
       segment_osrm_time
0                 1008.0
1                   65.0
2                 1941.0
```

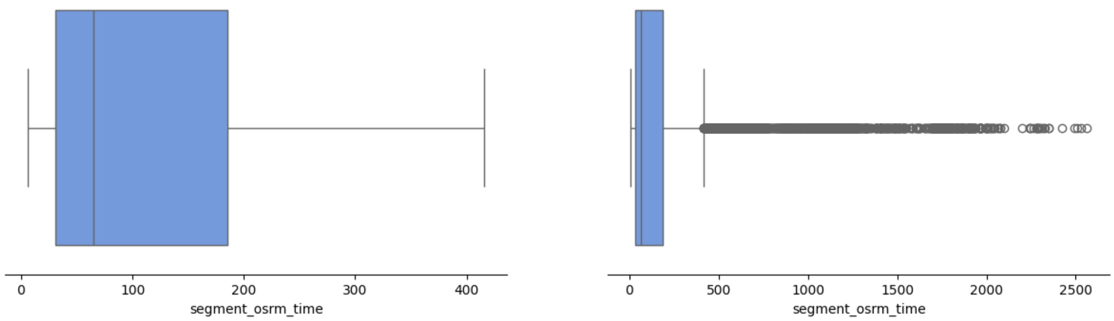
```
3                    16.0
4                   115.0
…                   …
14812                62.0
14813                11.0
14814                88.0
14815               221.0
14816                67.0

[14817 rows x 1 columns]
```

Clipped data of segment_osrm_time

```
       segment_osrm_time
0                   416.0
1                    65.0
2                   416.0
3                    16.0
4                   115.0
…                   …
14812                62.0
14813                11.0
14814                88.0
14815               221.0
14816                67.0

[14817 rows x 1 columns]
```

Filtered data of segment_osrm_time

```
       segment_osrm_time
0                  1008.0
1                    65.0
2                  1941.0
3                    16.0
4                   115.0
…                   …
14812                62.0
14813                11.0
14814                88.0
14815               221.0
14816                67.0

[14817 rows x 1 columns]
```




```
       segment_osrm_distance
0                1320.473267
1                  84.189400
2                2545.267822
3                  19.876600
4                 146.791901
…                        …
14812              64.855103
14813              16.088299
14814             104.886597
14815             223.532394
14816              80.578705

[14817 rows x 1 columns]
```

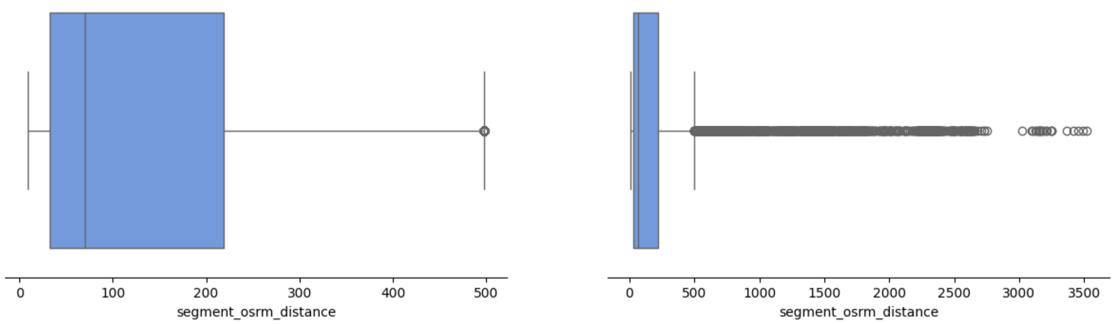
Clipped data of segment_osrm_distance

```
       segment_osrm_distance
0                 498.024261
1                  84.189400
2                 498.024261
3                  19.876600
4                 146.791901
…                        …
14812              64.855103
14813              16.088299
14814             104.886597
14815             223.532394
14816              80.578705

[14817 rows x 1 columns]
```

Filtered data of segment_osrm_distance

```
       segment_osrm_distance
```

```
0         1320.473267
1           84.189400
2         2545.267822
3           19.876600
4          146.791901
…                 …
14812       64.855103
14813       16.088299
14814      104.886597
14815      223.532394
14816       80.578705

[14817 rows x 1 columns]
```



[394]:

```
num_df = df2[num_cols]
num_df
```

[394]:

```
       od_total_time  start_scan_to_end_scan  actual_distance_to_destination  \
0            2260.11                  2259.0                      824.732849
1             181.61                   180.0                       73.186905
2            3934.36                  3933.0                     1927.404297
3             100.49                   100.0                       17.175274
4             718.34                   717.0                      127.448502
…                 …                      …                               …
14812         258.03                   257.0                       57.762333
14813          60.59                    60.0                       15.513784
14814         422.12                   421.0                       38.684837
14815         348.52                   347.0                      134.723831
14816         354.40                   353.0                       66.081528

       actual_time  osrm_time  osrm_distance  segment_actual_time  \
0           1562.0      717.0     991.352295               1548.0
```

```
1            143.0      68.0     85.111000               141.0
2           3347.0    1740.0   2354.066650              3308.0
3             59.0      15.0     19.680000                59.0
4            341.0     117.0    146.791794               340.0
…              …        …           …                  …
14812         83.0      62.0     73.462997                82.0
14813         21.0      12.0     16.088200                21.0
14814        282.0      48.0     58.903702               281.0
14815        264.0     179.0    171.110306               258.0
14816        275.0      68.0     80.578705               274.0

       segment_osrm_time  segment_osrm_distance
0                 1008.0            1320.473267
1                   65.0              84.189400
2                 1941.0            2545.267822
3                   16.0              19.876600
4                  115.0             146.791901
…                    …                   …
14812               62.0              64.855103
14813               11.0              16.088299
14814               88.0             104.886597
14815              221.0             223.532394
14816               67.0              80.578705

[14817 rows x 9 columns]
```

[395]:
```
num_cols
```

[395]:
```
['od_total_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']
```

[396]:
```
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_total_time  start_scan_to_end_scan  actual_distance_to_destination  \
0         691.990952              691.990952                      691.990952   
1         181.610000              180.000000                       73.186905   
2         691.990952              691.990952                      691.990952   
3         100.490000              100.000000                       17.175274   
4         691.990952              691.990952                      127.448502   
…                …                     …                             …   
14812     258.030000              257.000000                       57.762333   
14813      60.590000               60.000000                       15.513784   
14814     422.120000              421.000000                       38.684837   
14815     348.520000              347.000000                      134.723831   
14816     354.400000              353.000000                       66.081528   

       actual_time   osrm_time  osrm_distance  segment_actual_time  \
0       691.990952  691.990952     691.990952           691.990952   
1       143.000000   68.000000      85.111000           141.000000   
2       691.990952  691.990952     691.990952           691.990952   
3        59.000000   15.000000      19.680000            59.000000   
4       341.000000  117.000000     146.791794           340.000000   
…             …          …            …                   …   
14812    83.000000   62.000000      73.462997            82.000000   
14813    21.000000   12.000000      16.088200            21.000000   
14814   282.000000   48.000000      58.903702           281.000000   
14815   264.000000  179.000000     171.110306           258.000000   
14816   275.000000   68.000000      80.578705           274.000000   

       segment_osrm_time  segment_osrm_distance  
0             691.990952             691.990952  
1              65.000000              84.189400  
2             691.990952             691.990952  
3              16.000000              19.876600  
4             115.000000             146.791901  
…                  …                      …  
14812          62.000000              64.855103  
14813          11.000000              16.088299  
14814          88.000000             104.886597  
14815         221.000000             223.532394  
14816          67.000000              80.578705  

[14817 rows x 9 columns]
       od_total_time  start_scan_to_end_scan  actual_distance_to_destination  \
0            2260.11                  2259.0                      824.732849   
1             181.61                   180.0                       73.186905   
2            3934.36                  3933.0                     1927.404297   
3             100.49                   100.0                       17.175274   
```

```
4         718.34                  717.0                     127.448502
…          …                    …                             …
14812     258.03                  257.0                      57.762333
14813      60.59                   60.0                      15.513784
14814     422.12                  421.0                      38.684837
14815     348.52                  347.0                     134.723831
14816     354.40                  353.0                      66.081528

       actual_time  osrm_time  osrm_distance  segment_actual_time  \
0           1562.0      717.0     991.352295               1548.0
1            143.0       68.0      85.111000                141.0
2           3347.0     1740.0    2354.066650               3308.0
3             59.0       15.0      19.680000                 59.0
4            341.0      117.0     146.791794                340.0
…             …          …            …                     …
14812         83.0       62.0      73.462997                 82.0
14813         21.0       12.0      16.088200                 21.0
14814        282.0       48.0      58.903702                281.0
14815        264.0      179.0     171.110306                258.0
14816        275.0       68.0      80.578705                274.0

       segment_osrm_time  segment_osrm_distance
0                 1008.0            1320.473267
1                   65.0              84.189400
2                 1941.0            2545.267822
3                   16.0              19.876600
4                  115.0             146.791901
…                   …                    …
14812               62.0              64.855103
14813               11.0              16.088299
14814               88.0             104.886597
14815              221.0             223.532394
14816               67.0              80.578705

[14817 rows x 9 columns]
```

1.4 In-depth analysis and feature engineering

Compare the difference between od_total_time and start_scan_to_end_scan. Do hypothesis testing/ Visual analysis to check.

STEP-1 : Set up Null Hypothesis

Null Hypothesis (H0) - od_total_time (Total Trip Time) and start_scan_to_end_scan (Expected total trip time) are same.

Alternate Hypothesis (Ha) - od_total_time (Total Trip Time) and start_scan_to_end_scan (Expected total trip time) are different.

STEP-2 : Checking for basic assumpitons for the hypothesis

- Distribution check using **QQ Plot**
- Homogeneity of Variances using **Lavene's test**

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

If the assumptions of T Test are met then we can proceed performing T Test for independent samples else we will perform the non parametric test equivalent to T Test for independent sample i.e., Mann-Whitney U rank test for two independent samples.

STEP-4: Compute the p-value and fix value of alpha.

- We set our alpha to be 0.05

STEP-5: Compare p-value and alpha.

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

- p-val > alpha : Accept H0
- p-val < alpha : Reject H0

[397]:
```
clipped_num_df[['od_total_time', 'start_scan_to_end_scan']].describe()
```

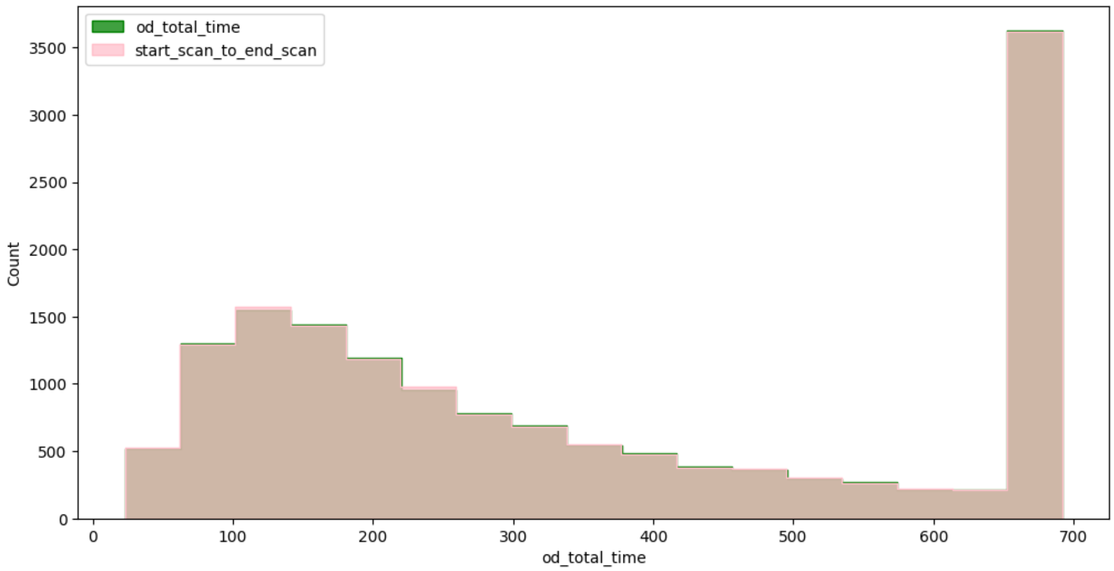
[397]:

	od_total_time	start_scan_to_end_scan
count	14817.000000	14817.000000
mean	354.232826	353.645472
std	231.808000	231.931918
min	23.460000	23.000000
25%	149.930000	149.000000
50%	280.770000	280.000000
75%	638.200000	637.000000
max	691.990952	691.990952

Insight: Visual Tests to know if the samples follow normal distribution

[398]:
```
plt.figure(figsize = (12, 6))
sns.histplot(clipped_num_df['od_total_time'], element = 'step', color = 'green')
sns.histplot(clipped_num_df['start_scan_to_end_scan'], element = 'step', color␣
 ↪= 'pink')
plt.legend(['od_total_time', 'start_scan_to_end_scan'])
plt.plot()
```

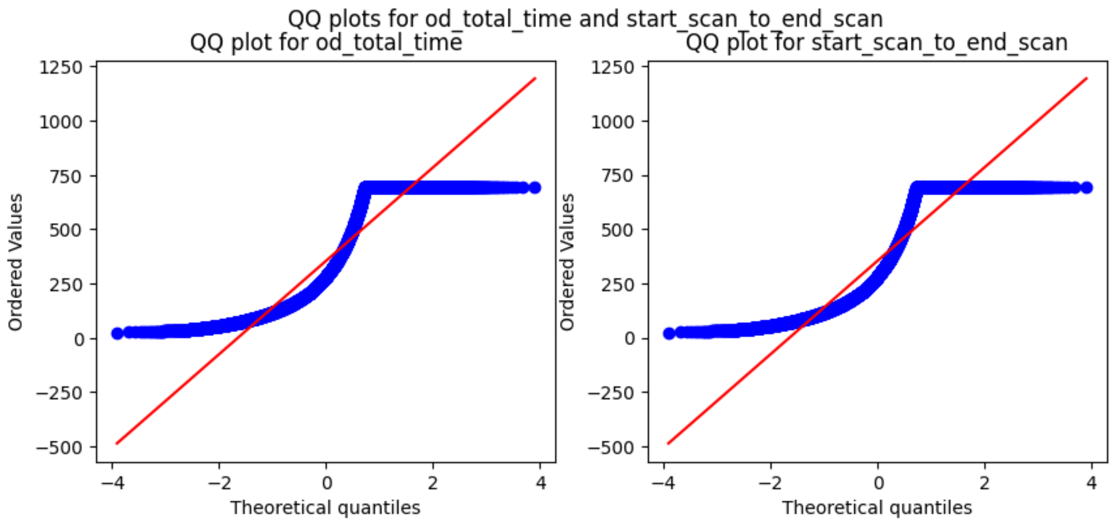
[398]: []



Distribution check using QQ Plot

[399]:
```
plt.figure(figsize = (10, 4))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for od_total_time and start_scan_to_end_scan')
spy.probplot(clipped_num_df['od_total_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for od_total_time')
plt.subplot(1, 2, 2)
spy.probplot(clipped_num_df['start_scan_to_end_scan'], plot = plt, dist =␣
↪'norm')
plt.title('QQ plot for start_scan_to_end_scan')
plt.plot()
```

[399]: []

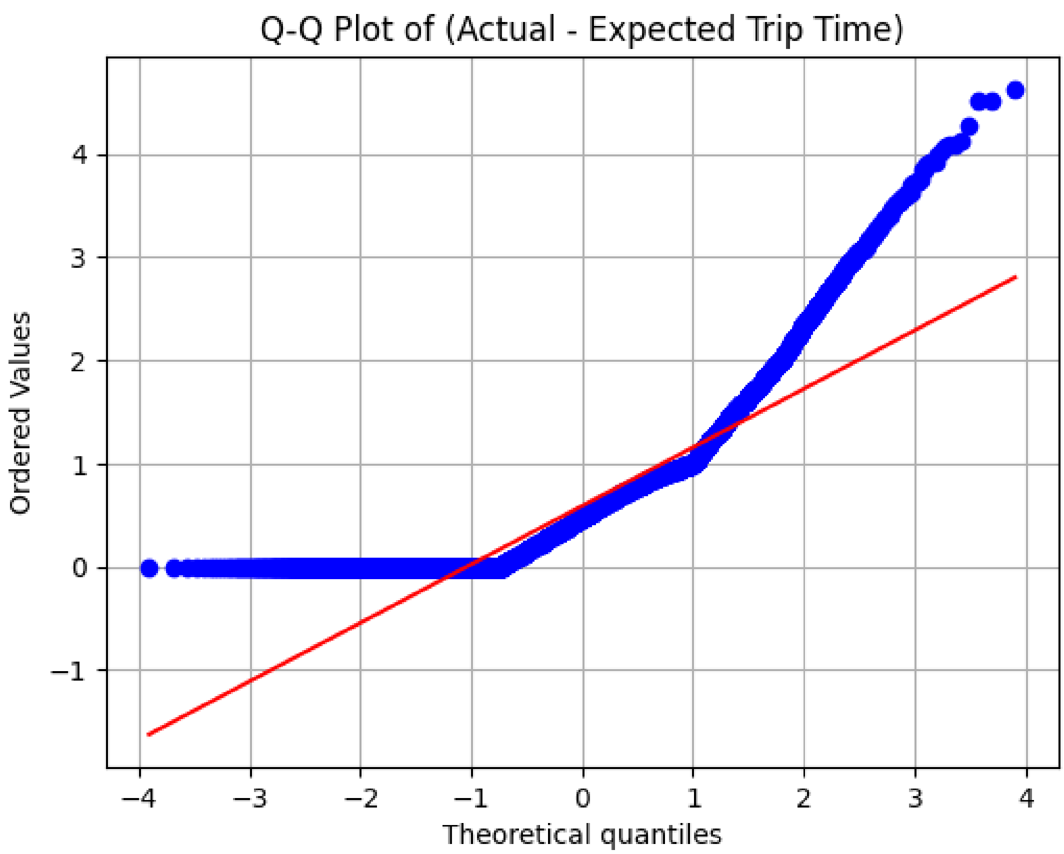


Insight: from the above plots that the samples do not come from normal distribution.

[400]:
```
df_clipped = clipped_num_df.copy()
```

[401]:
```
df_clipped['difference'] = df_clipped['od_total_time'] -
    ↪df_clipped['start_scan_to_end_scan']
```

[402]:
```
spy.probplot(df_clipped['difference'].dropna(), dist="norm", plot=plt)
plt.title('Q-Q Plot of (Actual - Expected Trip Time)')
plt.grid()
plt.show()
```



Insight: QQ-Plot concludes that data is not normal.

Lets Perform Shapiro-Wilk Test for normality.

[403]:
```
test_stat, p_value = spy.shapiro(df_clipped['od_total_time'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 1.3419821706632396e-55
The sample does not follow normal distribution
```

[404]:
```
test_stat, p_value = spy.shapiro(df_clipped['start_scan_to_end_scan'].
 ↪sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 1.8162044703153615e-55
The sample does not follow normal distribution
```

Insight: Shapiro Wilk alos concludes Data is not Normally Distrubuted.

Lets try to use Log Normal or Box Cox Transformations:

[405]:
```
skewness = df_clipped[numerical_columns].skew()  # For numerical columns in df
print("Skewness:\n", skewness)
```

```
Skewness:
 od_total_time                    0.397086
start_scan_to_end_scan          0.399477
actual_distance_to_destination  2.088891
actual_time                     0.973901
osrm_time                       2.050116
osrm_distance                   1.759630
segment_actual_time             0.983961
segment_osrm_time               1.914626
segment_osrm_distance           1.682813
dtype: float64
```

Insights:

1. Most of Data is heavily Right Skewed, we are good to use Log Normal .

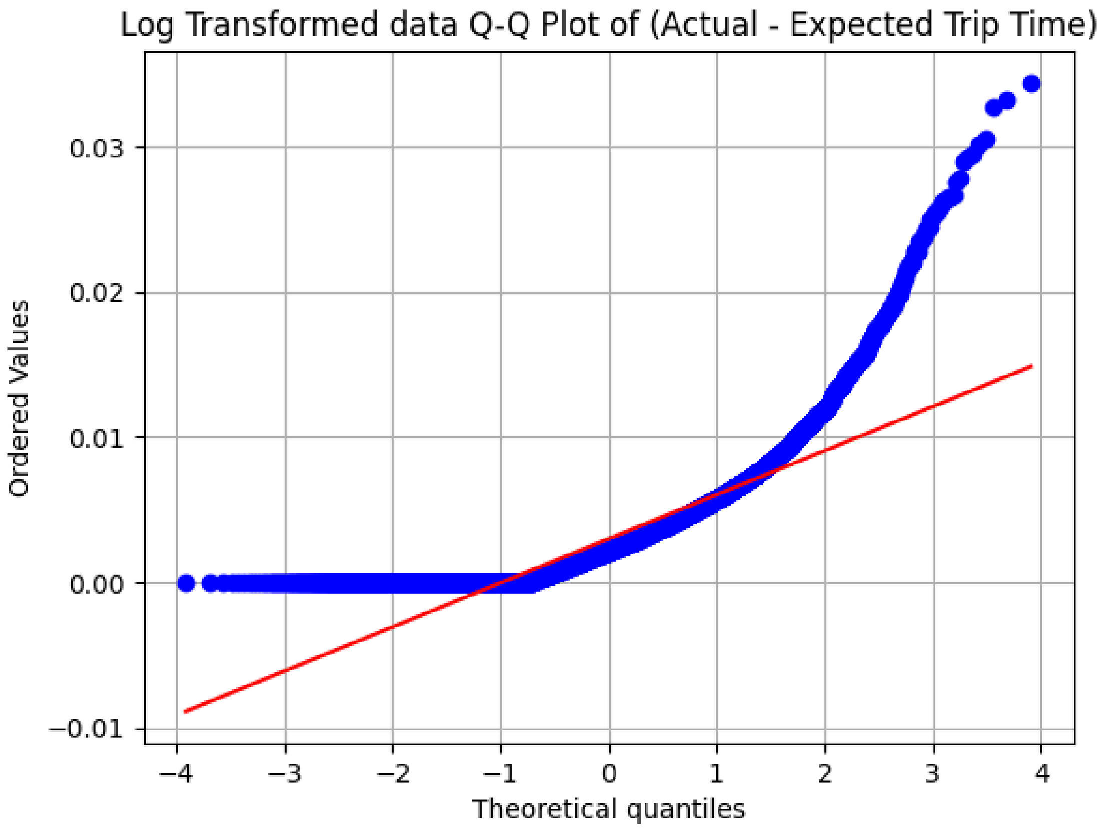
[406]:
```
all_positive = (df_clipped[numerical_columns] > 0).all().all()  # Returns True␣
↪if all values are positive, False otherwise
print("All values are positive:", all_positive)
```

```
All values are positive: True
```

Insight: All values are positive can use Box-Cox Transformation also

[407]:
```
log_data =  np.log(df_clipped[['od_total_time','start_scan_to_end_scan']])
```

[408]:
```
log_data['difference'] = log_data['od_total_time'] -␣
↪log_data['start_scan_to_end_scan']

spy.probplot(log_data['difference'].dropna(), dist="norm", plot=plt)
plt.title('Log Transformed data Q-Q Plot of (Actual - Expected Trip Time)')
plt.grid()
plt.show()
```



Transforming the data using boxcox transformation to check if the transformed data follows normal distribution.

[409]:
```
transformed_od_total_time = spy.boxcox(df_clipped['od_total_time'])[0]
test_stat, p_value = spy.shapiro(transformed_od_total_time)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 9.484491345715386e-66
The sample does not follow normal distribution
```

[410]:
```
transformed_start_scan_to_end_scan = spy.
↪boxcox(df_clipped['start_scan_to_end_scan'])[0]
test_stat, p_value = spy.shapiro(transformed_start_scan_to_end_scan)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
```

```
    print('The sample follows normal distribution')
```

```
p-value 1.117654540600476e-65
The sample does not follow normal distribution
```

Insight: Even after applying the boxcox transformation and Log Normal Transformation on each of the "od_total_time" and "start_scan_to_end_scan" columns, the distributions do not follow normal distribution.

Homogeneity of Variances using Lavene's test

[411]:
```
# Null Hypothesis(HO) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = spy.levene(df_clipped['od_total_time'],␣
 ↪df_clipped['start_scan_to_end_scan'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples do not have  Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 0.9938910188261746
The samples have Homogenous Variance
```

Since the samples are not normally distributed, T-Test cannot be applied here, we can perform its non parametric equivalent test i.e., Mann-Whitney U rank test for two independent samples.

[412]:
```
test_stat, p_value = spy.mannwhitneyu(df_clipped['od_total_time'],␣
 ↪df_clipped['start_scan_to_end_scan'])
print('P-value :',p_value)
```

```
P-value : 0.7909505580544021
```

Since p-value > alpha therfore it can be concluded that od_total_time and start_scan_to_end_scan are similar.

Do hypothesis testing/ visual analysis between actual_time aggregated value and segment actual time aggregated value (aggregated values are the values you'll get after merging the rows on the basis of trip_uuid)

[413]:
```
df_clipped[['actual_time', 'segment_actual_time']].describe()
```

[413]:

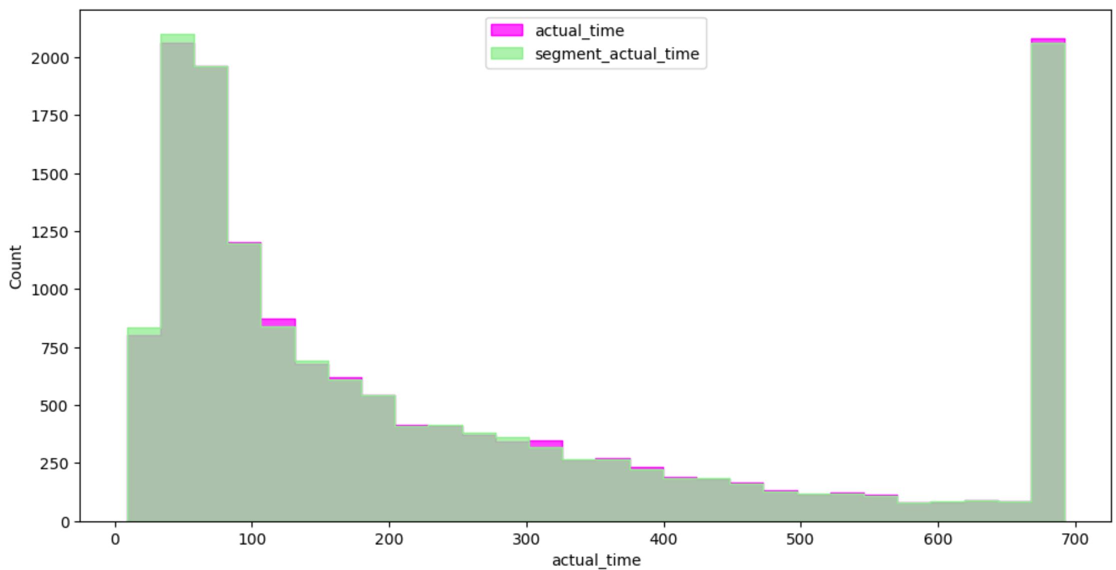
	actual_time	segment_actual_time
count	14817.000000	14817.000000
mean	247.563121	246.093873
std	227.586605	227.355223
min	9.000000	9.000000

```
25%       67.000000            66.000000
50%      149.000000           147.000000
75%      370.000000           367.000000
max      691.990952           691.990952
```

Visual Tests to know if the samples follow normal distribution

[414]:
```
plt.figure(figsize = (12, 6))
sns.histplot(df_clipped['actual_time'], element = 'step', color = 'magenta')
sns.histplot(df_clipped['segment_actual_time'], element = 'step', color =␣
 ↪'lightgreen')
plt.legend(['actual_time', 'segment_actual_time'])
plt.plot()
```

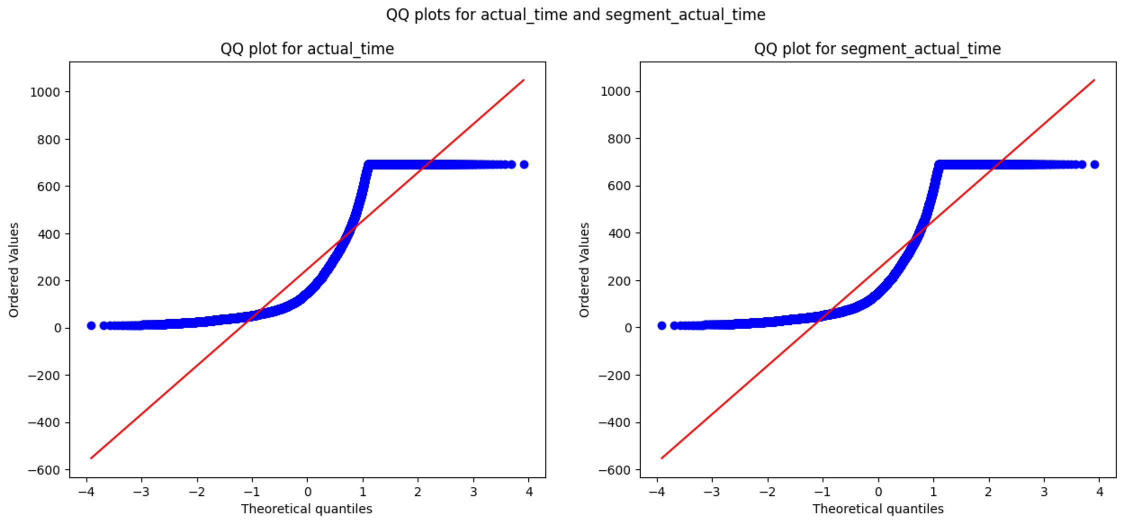
[414]: []



Distribution check using QQ Plot

[415]:
```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for actual_time and segment_actual_time')
spy.probplot(df_clipped['actual_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for actual_time')
plt.subplot(1, 2, 2)
spy.probplot(df_clipped['segment_actual_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_actual_time')
plt.plot()
```

[415]: []



Insight:

from the above plots that the samples do not come from normal distribution.

Applying Shapiro-Wilk test for normality

H0 : The sample follows normal distribution Ha : The sample does not follow normal distribution

alpha = 0.05

Test Statistics : Shapiro-Wilk test for normality

[416]:
```
test_stat, p_value = spy.shapiro(df_clipped['actual_time'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 3.8758397250790774e-61
The sample does not follow normal distribution
```

[417]:
```
test_stat, p_value = spy.shapiro(df_clipped['segment_actual_time'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 1.5865374416394726e-60
The sample does not follow normal distribution
```

Transforming the data using boxcox transformation to check if the transformed data follows normal distribution.

[418]:
```
transformed_actual_time = spy.boxcox(df_clipped['actual_time'])[0]
test_stat, p_value = spy.shapiro(transformed_actual_time)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 7.465938752250912e-56
The sample does not follow normal distribution
```

[419]:
```
transformed_segment_actual_time = spy.
 ↪boxcox(df_clipped['segment_actual_time'])[0]
test_stat, p_value = spy.shapiro(transformed_segment_actual_time)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 9.520331428691678e-56
The sample does not follow normal distribution
```

Even after applying the boxcox transformation on each of the "actual_time" and "segment_actual_time" columns, the distributions do not follow normal distribution.

Homogeneity of Variances using Lavene's test

[420]:
```
# Null Hypothesis(H0) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = spy.levene(df_clipped['actual_time'],␣
 ↪df_clipped['segment_actual_time'])
print('p-value', p_value)

if p_value < 0.05:
    print('The samples do not have Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 0.7682211083093626
The samples have Homogenous Variance
```

Since the samples do not come from normal distribution T-Test cannot be applied here, we can perform its non parametric equivalent test i.e., Mann-Whitney U rank test for two independent samples.

[421]:
```
test_stat, p_value = spy.mannwhitneyu(df_clipped['actual_time'],␣
↪df_clipped['segment_actual_time'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples are not similar')
else:
    print('The samples are similar ')
```

```
p-value 0.42108476986607957
The samples are similar
```

Since p-value > alpha therfore it can be concluded that actual_time and segment_actual_time are similar.

Do hypothesis testing/ visual analysis between osrm distance aggregated value and segment osrm distance aggregated value (aggregated values are the values you'll get after merging the rows on the basis of trip_uuid)

[422]:
```
df_clipped[['osrm_distance', 'segment_osrm_distance']].describe()
```

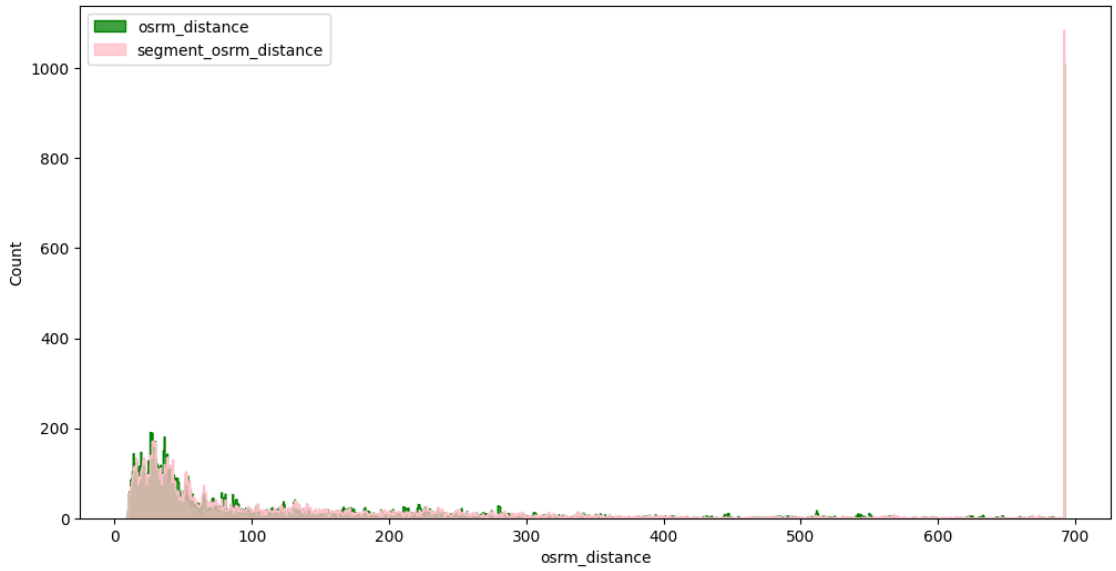
[422]:

	osrm_distance	segment_osrm_distance
count	14817.000000	14817.000000
mean	156.343278	163.876332
std	192.611962	196.932752
min	9.072900	9.072900
25%	30.819201	32.654499
50%	65.618805	70.154404
75%	208.475006	218.802399
max	691.990952	691.990952

Visual Tests to know if the samples follow normal distribution

[423]:
```
plt.figure(figsize = (12, 6))
sns.histplot(df_clipped['osrm_distance'], element = 'step', color = 'green',␣
↪bins = 1000)
sns.histplot(df_clipped['segment_osrm_distance'], element = 'step', color =␣
↪'pink', bins = 1000)
plt.legend(['osrm_distance', 'segment_osrm_distance'])
plt.plot()
```

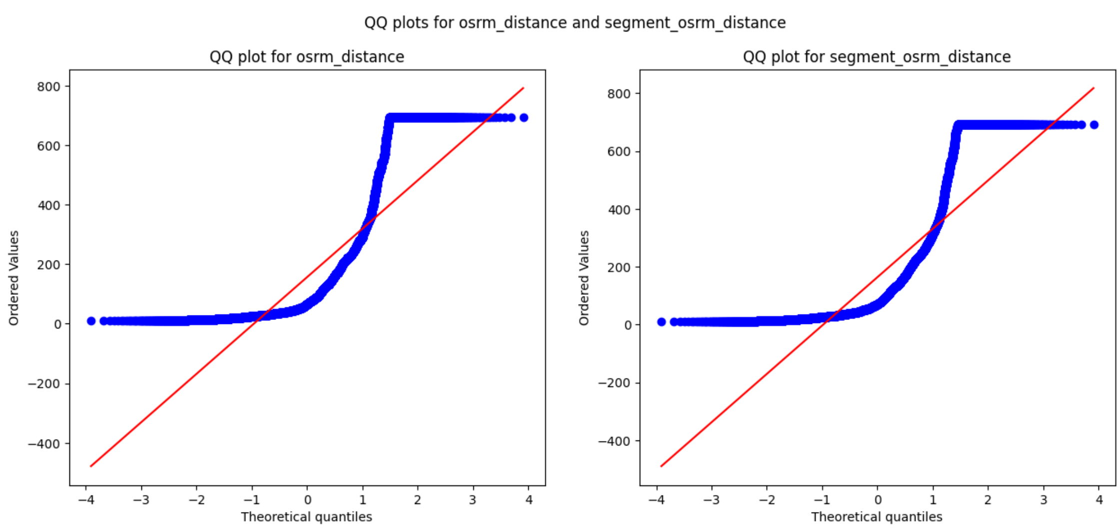
[423]: []



Distribution check using QQ Plot

[424]:
```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for osrm_distance and segment_osrm_distance')
spy.probplot(df_clipped['osrm_distance'], plot = plt, dist = 'norm')
plt.title('QQ plot for osrm_distance')
plt.subplot(1, 2, 2)
spy.probplot(df_clipped['segment_osrm_distance'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_osrm_distance')
plt.plot()
```

[424]: []



It can be seen from the above plots that the samples do not come from normal distribution.

Applying Shapiro-Wilk test for normality H0 : The sample follows normal distribution Ha : The sample does not follow normal distribution

alpha = 0.05

Test Statistics : Shapiro-Wilk test for normality

[425]:
```
test_stat, p_value = spy.shapiro(df_clipped['osrm_distance'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 1.1687551780281063e-68
The sample does not follow normal distribution
```

[426]:
```
test_stat, p_value = spy.shapiro(df_clipped['segment_osrm_distance'].
 ↪sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 2.883051485231325e-68
The sample does not follow normal distribution
```

Transforming the data using boxcox transformation to check if the transformed data follows normal distribution.

[427]:
```
transformed_osrm_distance = spy.boxcox(df_clipped['osrm_distance'])[0]
test_stat, p_value = spy.shapiro(transformed_osrm_distance)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 7.542802000057594e-51
The sample does not follow normal distribution
```

[428]:
```
transformed_segment_osrm_distance = spy.
 ↪boxcox(df_clipped['segment_osrm_distance'])[0]
test_stat, p_value = spy.shapiro(transformed_segment_osrm_distance)
print('p-value', p_value)
```

```
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 2.1641731490105593e-50
The sample does not follow normal distribution
```

Even after applying the boxcox transformation on each of the "osrm_distance" and "segment_osrm_distance" columns, the distributions do not follow normal distribution.

Homogeneity of Variances using Lavene's test

[429]:
```
# Null Hypothesis(HO) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = spy.levene(df_clipped['osrm_distance'],␣
 ↪df_clipped['segment_osrm_distance'])
print('p-value', p_value)

if p_value < 0.05:
    print('The samples do not have Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 0.013039732360819787
The samples do not have Homogenous Variance
```

Since the samples do not follow any of the assumptions, T-Test cannot be applied here. We can perform its non parametric equivalent test i.e., Mann-Whitney U rank test for two independent samples.

[430]:
```
test_stat, p_value = spy.mannwhitneyu(df_clipped['osrm_distance'],␣
 ↪df_clipped['segment_osrm_distance'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples are not similar')
else:
    print('The samples are similar ')
```

```
p-value 1.3056583795241463e-06
The samples are not similar
```

Since p-value < alpha therfore it can be concluded that osrm_distance and segment_osrm_distance are not similar.

Do hypothesis testing/ visual analysis between osrm time aggregated value and segment osrm time aggregated value (aggregated values are the values you'll get after merging the rows on the basis of trip_uuid)

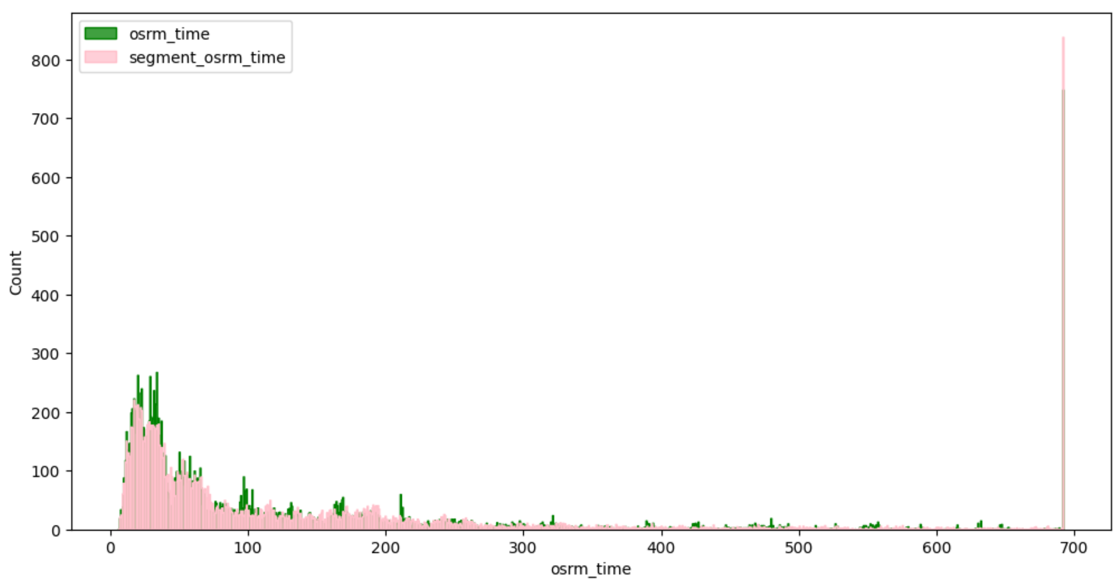
[431]:
```
df_clipped[['osrm_time', 'segment_osrm_time']].describe().T
```

[431]:
```
                     count        mean         std  min   25%   50%    75%  \
osrm_time          14817.0  137.033558  175.338338  6.0  29.0  60.0  168.0
segment_osrm_time  14817.0  147.060431  182.784183  6.0  31.0  65.0  185.0

                          max
osrm_time          691.990952
segment_osrm_time  691.990952
```

Visual Tests to know if the samples follow normal distribution

[432]:
```
plt.figure(figsize = (12, 6))
sns.histplot(df_clipped['osrm_time'], element = 'step', color = 'green', bins =␣
 ↪1000)
sns.histplot(df_clipped['segment_osrm_time'], element = 'step', color = 'pink',␣
 ↪bins = 1000)
plt.legend(['osrm_time', 'segment_osrm_time'])
plt.plot()
```

[432]: []

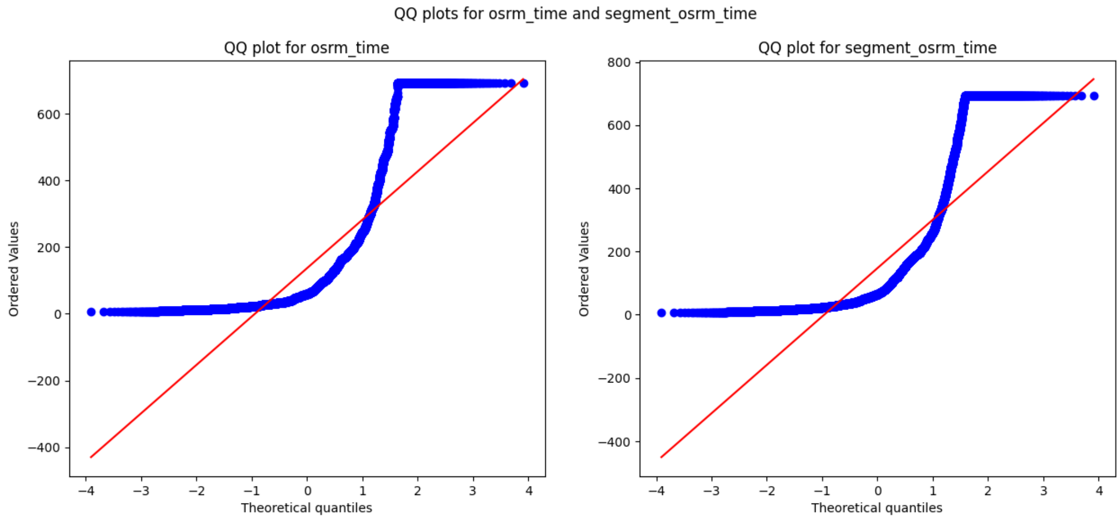


Distribution check using QQ Plot

[433]:
```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for osrm_time and segment_osrm_time')
spy.probplot(df_clipped['osrm_time'], plot = plt, dist = 'norm')
```

```
plt.title('QQ plot for osrm_time')
plt.subplot(1, 2, 2)
spy.probplot(df_clipped['segment_osrm_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_osrm_time')
plt.plot()
```

[433]: []



It can be seen from the above plots that the samples do not come from normal distribution.

Applying Shapiro-Wilk test for normality H0 : The sample follows normal distribution Ha : The sample does not follow normal distribution

alpha = 0.05

Test Statistics : Shapiro-Wilk test for normality

[434]:
```
test_stat, p_value = spy.shapiro(df_clipped['osrm_time'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 3.2837011030355646e-70
The sample does not follow normal distribution
```

[435]:
```
test_stat, p_value = spy.shapiro(df_clipped['segment_osrm_time'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
```

```
else:
    print('The sample follows normal distribution')
```

```
p-value 3.7593114670636977e-69
The sample does not follow normal distribution
```

Transforming the data using boxcox transformation to check if the transformed data follows normal distribution.

[436]:
```
transformed_osrm_time = spy.boxcox(df_clipped['osrm_time'])[0]
test_stat, p_value = spy.shapiro(transformed_osrm_time)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 9.072210814383864e-44
The sample does not follow normal distribution
```

[437]:
```
transformed_segment_osrm_time = spy.boxcox(df_clipped['segment_osrm_time'])[0]
test_stat, p_value = spy.shapiro(transformed_segment_osrm_time)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 7.146068328501078e-45
The sample does not follow normal distribution
```

Even after applying the boxcox transformation on each of the “osrm_time” and “segment_osrm_time” columns, the distributions do not follow normal distribution.

Homogeneity of Variances using Lavene’s test

[438]:
```
# Null Hypothesis(HO) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = spy.levene(df_clipped['osrm_time'],
 ↪df_clipped['segment_osrm_time'])
print('p-value', p_value)

if p_value < 0.05:
    print('The samples do not have Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 2.534993864187712e-05
The samples do not have Homogenous Variance
```

Since the samples do not follow any of the assumptions, T-Test cannot be applied here. We can perform its non parametric equivalent test i.e., Mann-Whitney U rank test for two independent samples.

[439]:
```
test_stat, p_value = spy.mannwhitneyu(df_clipped['osrm_time'],␣
 ↪df_clipped['segment_osrm_time'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples are not similar')
else:
    print('The samples are similar ')
```

```
p-value 3.429029063678771e-08
The samples are not similar
```

Since p-value < alpha therfore it can be concluded that osrm_time and segment_osrm_time are not similar.

1.5 One-hot encoding on categorical variables

[440]:
```
encoded_df= df2.copy()
```

[441]:
```
# Get value counts after one-hot encoding

encoded_df['data'].value_counts()
```

[441]:
```
data
training    10654
test         4163
Name: count, dtype: int64
```

[442]:
```
encoded_df
```

[442]:
```
                      trip_uuid source_center destination_center      data  \
0      trip-153671041653548748  IND209304AAA       IND209304AAA  training
1      trip-153671042288605164  IND561203AAB       IND561203AAB  training
2      trip-153671043369099517  IND000000ACB       IND000000ACB  training
3      trip-153671046011330457  IND400072AAB       IND401104AAA  training
4      trip-153671052974046625  IND583101AAA       IND583119AAA  training
…                          …           …                …       …
14812  trip-153861095625827784  IND160002AAC       IND160002AAC      test
14813  trip-153861104386292051  IND121004AAB       IND121004AAA      test
14814  trip-153861106442901555  IND208006AAA       IND208006AAA      test
14815  trip-153861115439069069  IND627005AAA       IND628204AAA      test
14816  trip-153861118270144424  IND583119AAA       IND583119AAA      test
```

```
      route_type         trip_creation_time  \
0            FTL 2018-09-12 00:00:16.535741
1        Carting 2018-09-12 00:00:22.886430
2            FTL 2018-09-12 00:00:33.691250
3        Carting 2018-09-12 00:01:00.113710
4            FTL 2018-09-12 00:02:09.740725
…            …                          …
14812    Carting 2018-10-03 23:55:56.258533
14813    Carting 2018-10-03 23:57:23.863155
14814    Carting 2018-10-03 23:57:44.429324
14815    Carting 2018-10-03 23:59:14.390954
14816        FTL 2018-10-03 23:59:42.701692

                               source_name  \
0       Kanpur_Central_H_6 (Uttar Pradesh)
1        Doddablpur_ChikaDPP_D (Karnataka)
2            Gurgaon_Bilaspur_HB (Haryana)
3                 Mumbai Hub (Maharashtra)
4                   Bellary_Dc (Karnataka)
…                                        …
14812       Chandigarh_Mehmdpur_H (Punjab)
14813         FBD_Balabhgarh_DPC (Haryana)
14814   Kanpur_GovndNgr_DC (Uttar Pradesh)
14815  Tirunelveli_VdkkuSrt_I (Tamil Nadu)
14816        Sandur_WrdN1DPP_D (Karnataka)

                          destination_name  od_total_time  \
0       Kanpur_Central_H_6 (Uttar Pradesh)        2260.11
1        Doddablpur_ChikaDPP_D (Karnataka)         181.61
2            Gurgaon_Bilaspur_HB (Haryana)        3934.36
3          Mumbai_MiraRd_IP (Maharashtra)          100.49
4            Sandur_WrdN1DPP_D (Karnataka)         718.34
…                                        …            …
14812       Chandigarh_Mehmdpur_H (Punjab)         258.03
14813       Faridabad_Blbgarh_DC (Haryana)          60.59
14814   Kanpur_GovndNgr_DC (Uttar Pradesh)         422.12
14815  Tirchchndr_Shnmgprm_D (Tamil Nadu)          348.52
14816        Sandur_WrdN1DPP_D (Karnataka)         354.40

       start_scan_to_end_scan  …  destination_place  trip_creation_date  \
0                      2259.0  …         Central_H_6          2018-09-12
1                       180.0  …          ChikaDPP_D          2018-09-12
2                      3933.0  …         Bilaspur_HB          2018-09-12
3                       100.0  …           MiraRd_IP          2018-09-12
4                       717.0  …          WrdN1DPP_D          2018-09-12
…                         …  …                  …                  …
```

```
14812                  257.0  …         Mehmdpur_H          2018-10-03
14813                   60.0  …         Blbgarh_DC          2018-10-03
14814                  421.0  …       GovndNgr_DC           2018-10-03
14815                  347.0  …         Shnmgprm_D          2018-10-03
14816                  353.0  …         WrdN1DPP_D          2018-10-03

       trip_creation_day  trip_creation_month  trip_creation_year  \
0                     12                    9                2018
1                     12                    9                2018
2                     12                    9                2018
3                     12                    9                2018
4                     12                    9                2018
…                    …                    …                  …
14812                  3                   10                2018
14813                  3                   10                2018
14814                  3                   10                2018
14815                  3                   10                2018
14816                  3                   10                2018

       trip_creation_week  trip_creation_hour  \
0                      37                   0
1                      37                   0
2                      37                   0
3                      37                   0
4                      37                   0
…                     …                  …
14812                  40                  23
14813                  40                  23
14814                  40                  23
14815                  40                  23
14816                  40                  23

                                                corridor  \
0      Kanpur_Central_H_6 (Uttar Pradesh) <---> Kanpu…
1      Doddablpur_ChikaDPP_D (Karnataka) <---> Doddab…
2      Gurgaon_Bilaspur_HB (Haryana) <---> Gurgaon_Bi…
3      Mumbai Hub (Maharashtra) <---> Mumbai_MiraRd_I…
4      Bellary_Dc (Karnataka) <---> Sandur_WrdN1DPP_D…
…                                                  …
14812  Chandigarh_Mehmdpur_H (Punjab) <---> Chandigar…
14813  FBD_Balabhgarh_DPC (Haryana) <---> Faridabad_B…
14814  Kanpur_GovndNgr_DC (Uttar Pradesh) <---> Kanpu…
14815  Tirunelveli_VdkkuSrt_I (Tamil Nadu) <---> Tirc…
14816  Sandur_WrdN1DPP_D (Karnataka) <---> Sandur_Wrd…

                                          state_corridor  \
0      Uttar Pradesh--Kanpur <---> Uttar Pradesh--Kanpur
```

```
1      Karnataka--Doddablpur <---> Karnataka--Doddablpur
2                Haryana--Gurgaon <---> Haryana--Gurgaon
3          Maharashtra--Mumbai <---> Maharashtra--Mumbai
4             Karnataka--Bellary <---> Karnataka--Sandur
…                                                    …
14812         Punjab--Chandigarh <---> Punjab--Chandigarh
14813         Haryana--Faridabad <---> Haryana--Faridabad
14814  Uttar Pradesh--Kanpur <---> Uttar Pradesh--Kanpur
14815  Tamil Nadu--Tirunelveli <---> Tamil Nadu--Tirc…
14816           Karnataka--Sandur <---> Karnataka--Sandur

                                            city_corridor
0          Kanpur--Central_H_6 <---> Kanpur--Central_H_6
1      Doddablpur--ChikaDPP_D <---> Doddablpur--Chika…
2        Gurgaon--Bilaspur_HB <---> Gurgaon--Bilaspur_HB
3          Mumbai--unknown_place <---> Mumbai--MiraRd_IP
4                    Bellary--Dc <---> Sandur--WrdN1DPP_D
…                                                    …
14812  Chandigarh--Mehmdpur_H <---> Chandigarh--Mehmd…
14813  Faridabad--Balabhgarh_DPC <---> Faridabad--Blb…
14814      Kanpur--GovndNgr_DC <---> Kanpur--GovndNgr_DC
14815  Tirunelveli--VdkkuSrt_I <---> Tirchchndr--Shnm…
14816         Sandur--WrdN1DPP_D <---> Sandur--WrdN1DPP_D

[14817 rows x 32 columns]
```

[443]:
```python
# Get value counts before one-hot encoding

encoded_df['route_type'].value_counts()
```

[443]:
```
route_type
Carting    8908
FTL        5909
Name: count, dtype: int64
```

[444]:
```python
# Perform one-hot encoding on categorical column route type

from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
encoded_df['route_type'] = label_encoder.fit_transform(encoded_df['route_type'])
```

[445]:
```python
# Get value counts after one-hot encoding

encoded_df['route_type'].value_counts()
```

[445]:
```
route_type
0    8908
```

```
1    5909
Name: count, dtype: int64
```

[446]:
```python
# Get value counts of categorical variable 'data' before one-hot encoding

encoded_df['data'].value_counts()
```

[446]:
```
data
training    10654
test         4163
Name: count, dtype: int64
```

[447]:
```python
# Perform one-hot encoding on categorical variable 'data'
label_encoder = LabelEncoder()
encoded_df['data'] = label_encoder.fit_transform(encoded_df['data'])
```

1.6 Normalize/ Standardize the numerical features using MinMaxScaler or StandardScaler

[448]:
```python
from sklearn.preprocessing import MinMaxScaler

# Normalizing/Standardizing the numerical features using MinMaxScaler
min_max_scaler = MinMaxScaler()
min_max_scaled_numerical = min_max_scaler.fit_transform(encoded_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
```

[448]:

	od_total_time	start_scan_to_end_scan	actual_distance_to_destination	\
0	0.284016	0.283937	0.374613	
1	0.020082	0.019937	0.029476	
2	0.496617	0.496508	0.880999	
3	0.009781	0.009778	0.003753	
4	0.088238	0.088127	0.054395	
…	…	…	…	
14812	0.029786	0.029714	0.022392	
14813	0.004715	0.004698	0.002990	
14814	0.050623	0.050540	0.013631	
14815	0.041277	0.041143	0.057736	
14816	0.042024	0.041905	0.026213	

	actual_time	osrm_time	osrm_distance	segment_actual_time	\
0	0.248242	0.350938	0.346972	0.247388	
1	0.021419	0.030602	0.026859	0.021218	
2	0.533568	0.855874	0.828325	0.530301	
3	0.007992	0.004442	0.003747	0.008037	
4	0.053069	0.054788	0.048647	0.053207	

```
…          …          …            …                 …
14812      0.011829   0.027641     0.022745          0.011734
14813      0.001918   0.002962     0.002478          0.001929
14814      0.043638   0.020731     0.017602          0.043723
14815      0.040761   0.085390     0.057237          0.040026
14816      0.042519   0.030602     0.025258          0.042598

       segment_osrm_time  segment_osrm_distance
0               0.391712               0.373134
1               0.023065               0.021373
2               0.756450               0.721625
3               0.003909               0.003074
4               0.042611               0.039185
…                    …                    …
14812           0.021892               0.015872
14813           0.001955               0.001996
14814           0.032056               0.027262
14815           0.084050               0.061020
14816           0.023847               0.020346

[14817 rows x 9 columns]
```

1.7 Business Insights

EDA: 1. 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 2. The entire data is heavily right skewed 3. Almost all the features are heavy positively correleated with each other & which is intutive as well. 4. Start & End dates of the months have less percent of trips compare to mid of the month. Though the difference is not huge. 5. Thats very strange to see that there is absolutely no trip from 4th- 11th day of the month 6. Most orders come mid-month. That means customers usually make more orders in the mid of the month.

Route Type:

- The analysis shows that a greater share of shipments is handled via Full Truck Load (FTL) rather than carting, which has significant implications for enhancing delivery efficiency and speed.

Geographical Focus:

1. 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
2. Source Cities - Gurgaon, Bangalore, and Bhiwandi emerge as the busiest source cities, indicating their critical role in supporting overall business operations and transportation activities.
3. Destination Cities - Gurgaon, Bangalore, and Hyderabad are identified as the busiest destination cities, highlighting their importance in terms of business activities and population movement.

4. Busiest Corridor - The busiest transportation corridor is between Mumbai, Maharashtra and Bangalore, Karnataka, accounting for the highest number of trips.
5. Delivery Metrics Average Distance: 74.85 km Average Time: 5.35 hours
6. Delivery Time and Distance Accuracy
    - OSRM Estimated Time vs Actual Time: The mean actual delivery time is greater than the estimated OSRM time, indicating that OSRM tends to provide optimistic delivery estimates. This gap suggests potential delays in the real-world delivery process compared to initial projections.
    - OSRM Estimated Distance vs Actual Distance: The mean OSRM distance is higher than the actual distance traveled, suggesting a slight overestimation by the OSRM service. This discrepancy could affect route optimization and fuel efficiency calculations.
    - Segment-wise Time Analysis: The equality between the mean actual time and the segment-wise actual time indicates consistency in time measurements across different segments of the delivery process.
    - Segment-wise Distance Analysis: The mean segment-wise OSRM distance being greater than the overall OSRM distance suggests that OSRM provides more conservative distance estimates for individual segments.

Further Analysis:

1. Gaps in Trip Data: No trips are recorded between the 4th and 11th day of the month. Investigating the reasons for this gap could help uncover opportunities to boost order volume during this period.
2. Promotion of FTL (Full Truck Load) Handling: Given the strong usage of FTL routing, further initiatives to promote and optimize the FTL handling system could enhance operational efficiency and improve delivery performance.

1.8 Business Recommendations

Route Optimization:

- Optimize Karnataka's transportation network using route optimization algorithms and real-time traffic monitoring.
- Focus on Gurgaon and Bangalore with city-specific strategies to manage heavy traffic.

Operational Efficiency:

- Set more realistic delivery expectations, as actual delivery times exceed OSRM estimates.
- Refine distance estimations for better logistics planning and cost control.
- Implement demand forecasting to optimize resources during peak times.

Customer Satisfaction: * Improve accuracy in estimated delivery times and distances to enhance customer trust.

- Promote FTL shipments to ensure faster, more reliable deliveries.

Customer Profiling:

- Profile customers from Maharashtra, Karnataka, Haryana, Tamil Nadu, and Uttar Pradesh to better understand demand patterns and improve services.

Cost Optimization:

- Address discrepancies between estimated and actual times/distances for better resource planning and reduced operational costs.

Strategic Decision-Making:

- Regularly evaluate the preference for FTL to align logistics strategies with evolving business needs.

Collaboration with Stakeholders:

- Partner with government bodies, transport companies, and communities to manage and optimize traffic in key corridors and cities.