In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as st
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from statsmodels.graphics.gofplots import qqplot
import re
import os
```

In [2]:
```
import warnings
warnings.simplefilter('ignore')
os.chdir(r"D:\SCALERES\JupuyterNotebook\Delhivery")
```

In [3]:
```
df = pd.read_csv('delhivery_data.csv')
```

In [4]:
```
df.sample(5)
```

Out[4]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	dest
122606	training	2018-09-23 14:18:13.981195	thanos::sroute:bc7dbb1d-9379-4674-b8d3-f9c3b96...	FTL	trip-153771229398079221	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)	IN
29825	training	2018-09-15 20:09:00.426097	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153704214147054167	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)	IN
17283	test	2018-10-03 00:01:00.774939	thanos::sroute:38b8257c-1dae-4f7a-b762-009145e...	FTL	trip-153852486077464126	IND458664AAA	Neemuch_KarjuDPP_D (Madhya Pradesh)	IN
46455	test	2018-09-28 22:25:15.504856	thanos::sroute:caf62782-95cc-4d47-a071-d1c7038...	FTL	trip-153817351550461336	IND501359AAE	Hyderabad_Shamshbd_H (Telangana)	IN

34713	training	2018-09-19 19:53:42.622678	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	FTL	trip-153738682262223442	IND000000ACB	Gurgaon_Bilaspur_HB (Haryana)	IN

5 rows × 24 columns

Basic data cleaning and exploration

In [5]:
```
df.shape
# There are 1,44,867 rows and 24 columns in the dataset
```

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

- There are 1,44,867 rows and 24 columns in the dataset

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

Out[6]:
```
Index(['data', 'trip_creation_time', 'route_schedule_uuid', 'route_type',
       'trip_uuid', 'source_center', 'source_name', 'destination_center',
       'destination_name', 'od_start_time', 'od_end_time',
       'start_scan_to_end_scan', 'is_cutoff', 'cutoff_factor',
       'cutoff_timestamp', 'actual_distance_to_destination', 'actual_time',
       'osrm_time', 'osrm_distance', 'factor', 'segment_actual_time',
       'segment_osrm_time', 'segment_osrm_distance', 'segment_factor'],
      dtype='object')
```

In [7]:
```
unknown_columns = ['is_cutoff', 'cutoff_factor','cutoff_timestamp','factor','segment_factor']
```

- From the description of dataset, there are some unknown columns, dropping the unknown columns

In [8]:
```
# drooping unknown columns from the dataset
df.drop(columns=unknown_columns, inplace = True)
```

In [9]:
```
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  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  actual_distance_to_destination  144867 non-null  float64
 13  actual_time                     144867 non-null  float64
 14  osrm_time                       144867 non-null  float64
 15  osrm_distance                   144867 non-null  float64
 16  segment_actual_time             144867 non-null  float64
 17  segment_osrm_time               144867 non-null  float64
 18  segment_osrm_distance           144867 non-null  float64
dtypes: float64(8), object(11)
memory usage: 21.0+ MB
```

In [10]:
```
# converting the columns with two groups into Categorical
df['data'] = df['data'].astype('category')
df['route_type'] = df['route_type'].astype('category')
```

In [11]:
```
df['od_start_time'] = pd.to_datetime(df['od_start_time'])
df['od_end_time'] = pd.to_datetime(df['od_end_time'])
df['trip_creation_time'] = pd.to_datetime(df['trip_creation_time'], format='mixed')
```

In [12]:
```
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  float64
 12  actual_distance_to_destination  144867 non-null  float64
 13  actual_time                     144867 non-null  float64
 14  osrm_time                       144867 non-null  float64
 15  osrm_distance                   144867 non-null  float64
 16  segment_actual_time             144867 non-null  float64
 17  segment_osrm_time               144867 non-null  float64
 18  segment_osrm_distance           144867 non-null  float64
dtypes: category(2), datetime64[ns](3), float64(8), object(6)
memory usage: 19.1+ MB
```

In [13]:
```
df.describe().T
```

Out[13]:

	count	mean	min	25%	50%	75%
trip_creation_time	144867	2018-09-22 13:34:23.659819264	2018-09-12 00:00:16.535741	2018-09-17 03:20:51.775845888	2018-09-22 04:24:27.932764928	2018-09-27 17:57:56.350054912
od_start_time	144867	2018-09-22 18:02:45.855230720	2018-09-12 00:00:16.535741	2018-09-17 08:05:40.886155008	2018-09-22 08:53:00.116656128	2018-09-27 22:41:50.285857024
od_end_time	144867	2018-09-23 10:04:31.395393024	2018-09-12 00:50:10.814399	2018-09-18 01:48:06.410121984	2018-09-23 03:13:03.520212992	2018-09-28 12:49:06.054018048

start_scan_to_end_scan	144867.0	961.262986	20.0	161.0	449.0	1634.0
actual_distance_to_destination	144867.0	234.073372	9.000045	23.355874	66.126571	286.708875
actual_time	144867.0	416.927527	9.0	51.0	132.0	513.0
osrm_time	144867.0	213.868272	6.0	27.0	64.0	257.0
osrm_distance	144867.0	284.771297	9.0082	29.9147	78.5258	343.19325
segment_actual_time	144867.0	36.196111	-244.0	20.0	29.0	40.0
segment_osrm_time	144867.0	18.507548	0.0	11.0	17.0	22.0
segment_osrm_distance	144867.0	22.82902	0.0	12.0701	23.513	27.81325

In [14]:

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

Out[14]:

	count	unique	top	freq
route_schedule_uuid	144867	1504	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	1812
trip_uuid	144867	14817	trip-153811219535896559	101
source_center	144867	1508	IND000000ACB	23347
source_name	144574	1498	Gurgaon_Bilaspur_HB (Haryana)	23347
destination_center	144867	1481	IND000000ACB	15192
destination_name	144606	1468	Gurgaon_Bilaspur_HB (Haryana)	15192

Handle missing values

In [15]:

```
df.isna().sum()
```

```
Out[15]: 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
```

```
In [16]: df.isna().sum().sum()
```

```
Out[16]: 554
```

- total of 554 null values are in the dataset in Source columns and destination columns and They are contributing below 5 %
- Dropping the null value rows from the dataset

```
In [17]: # Dropping the data Missing values from Dataset
missing_index = df[df['source_name'].isna() | df['destination_name'].isna()].index
df.drop(missing_index, axis= 0, inplace=True)
```

```
In [18]: # after Dropping the Null values
df.isna().sum().sum()
```

```
Out[18]: 0
```

Aggregation on columns

In [19]:
```
numerical_cols = df.dtypes[df.dtypes == 'float']
categorical_col = df.dtypes[df.dtypes == 'category']
```

- **Groupby and Aggregations Trip_uuid, Source ID and Destination ID**

In [20]:
```
groups = ['trip_uuid', 'source_center', 'destination_center'] # list of columns for groupping
agg_func =  {'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'
        }


df_agg = df.groupby(groups).agg(agg_func).reset_index()
df_agg.sample(5)
```

Out[20]:

	trip_uuid	source_center	destination_center	data	route_type	trip_creation_time	source_name	des
13124	trip-153758865231525908	IND416510AAA	IND416606AAA	training	Carting	2018-09-22 03:57:32.315617	Sawantwadi_LaxmiNgr_D (Maharashtra)	Malva

9453	trip-153736774425928724	IND591115AAB	IND590016AAA	training	FTL	2018-09-19 14:35:44.259626	Kittur_ColageRD_D (Karnataka)	Belgaum_D
26070	trip-153860695642073919	IND741165AAB	IND742121AAB	test	Carting	2018-10-03 22:49:16.421019	Nazirpur_Central_D_1 (West Bengal)	Nowda_ (
22842	trip-153834469166488572	IND273014AAB	IND277303AAC	test	FTL	2018-09-30 21:58:11.665206	Gorakhpur_Matriprm_IP (Uttar Pradesh)	Sikandarpur (U
13355	trip-153761003705592923	IND787001AAA	IND787057AAA	training	FTL	2018-09-22 09:53:57.056177	LakhimpurN_SashPhkn_D (Assam)	Dhemaj

In [21]:
```
df_agg['od_total_time'] = df_agg['od_end_time'] - df_agg['od_start_time']
df_agg.drop(columns = ['od_end_time', 'od_start_time'], inplace = True)
df_agg['od_total_time'] = df_agg['od_total_time'].apply(lambda x : round(x.total_seconds() / 60.0, 2))
df_agg['od_total_time'].head()
```

Out[21]:
```
0    1260.60
1     999.51
2      58.83
3     122.78
4     834.64
Name: od_total_time, dtype: float64
```

- Aggregation on the basis of just Trip_uuid

In [22]:
```
agg_func =  {'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'
        }


df_aggid = df_agg.groupby('trip_uuid').agg(agg_func).reset_index()
df_aggid.head()
```

Out[22]:

	trip_uuid	source_center	destination_center	data	route_type	trip_creation_time	source_name	destinati
0	trip-153671041653548748	IND209304AAA	IND209304AAA	training	FTL	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	Kanpur_Cer (Uttar
1	trip-153671042288605164	IND561203AAB	IND561203AAB	training	Carting	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	Doddablpur_Chik (Ka
2	trip-153671043369099517	IND000000ACB	IND000000ACB	training	FTL	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)	Gurgaon_Bila (I
3	trip-153671046011330457	IND400072AAB	IND401104AAA	training	Carting	2018-09-12 00:01:00.113710	Mumbai Hub (Maharashtra)	Mumbai_M (Mah
4	trip-153671052974046625	IND583101AAA	IND583119AAA	training	FTL	2018-09-12 00:02:09.740725	Bellary_Dc (Karnataka)	Sandur_WrdN (Ka

Feature Engineering

- **Function for extracting States**

In [23]:
```
def get_state(name):
    '''The function helps to extract states names from the columns'''
    try:
```

```
        if pd.isna(name):
            return None
        pattern = r"\([A-Za-z &]+\s?\w+\)"
        match = re.findall(pattern, str(name))
        if match:
            state = match[0].replace("(", "").replace(")", "")
            return state
        return None
    except exception as e:
        print(f'The error is {e}')
```

- Function for extracting cities

In [24]:

```
def get_city(name):
    '''this function helps to split the city name form the columns '''
    if pd.isna(name):
        return None

    pattern = r"\([A-Za-z &]+\s?\w+\)"
    matches = re.findall(pattern, str(name))

    if not matches:
        return name

    state = matches[0]
    city_place_code = name.replace(state, '').strip()
    city_place_code_parts = city_place_code.split("_")

    if len(city_place_code_parts) == 1:
        city = city_place_code_parts[0].strip()
    elif len(city_place_code_parts) == 2:
        city = city_place_code.strip()
    elif len(city_place_code_parts) in [3, 4]:
        city = city_place_code_parts[0].strip()
    else:
        city = city_place_code

    return city
```

- Function for extracting places

In [25]:
```python
def get_place(name):
    '''This function helps in splitting the places of from the passied columns '''
    pattern="\([A-Za-z &]+\s?\w+\)"
    try:
        state=re.findall(pattern, name)[0]
        city_place_code=name.replace(state,'')
        city_place_code_parts=city_place_code.split("_")
        if len(city_place_code_parts)==3 or len(city_place_code_parts)==4:
            place=city_place_code_parts[1].strip()
        else:
            place=None
        return place
    except Exception as exp:
        return None
```

- Function for extracting codes

In [26]:
```python
def get_code(name):
    '''This Function helps for splitting code from the columns'''
    pattern="\([A-Za-z &]+\s?\w+\)"
    try:
        state=re.findall(pattern, name)[0]
        city_place_code=name.replace(state,'')
        city_place_code_parts=city_place_code.split("_")
        if len(city_place_code_parts)==3 :
            code=city_place_code_parts[2].strip()
        elif  len(city_place_code_parts)==4:
            code="_".join(city_place_code_parts[2:]).strip()
        else:
            code=None
        return code
    except Exception as exp:
        return None
```

Applying the functions

Applying the on Source Column

In [27]:
```
df_aggid['source_state'] = df_aggid['source_name'].map(get_state)
df_aggid['source_state'].sample(5)
```

Out[27]:
```
3201          Haryana
551       West Bengal
7905    Uttar Pradesh
4787        Karnataka
8214      Maharashtra
Name: source_state, dtype: object
```

In [28]:
```
df_aggid['source_city'] = df_aggid['source_name'].map(get_city)
df_aggid['source_city'].sample(5)
```

Out[28]:
```
12935    Bangalore
8421     Thuraiyur
12862      Kurnool
2046     Bengaluru
5155        Hoogly
Name: source_city, dtype: object
```

In [29]:
```
df_aggid['source_place'] = df_aggid['source_name'].map(get_place)
df_aggid['source_place'].sample(5)
```

Out[29]:
```
13639        None
6221        Alwal
6060     Trnsport
14099        None
10442       Bazar
Name: source_place, dtype: object
```

In [30]:
```
df_aggid['source_code'] = df_aggid['source_name'].map(get_code)
df_aggid['source_code'].sample(5)
```

Out[30]:
```
12901      I
5217      HB
2245      IP
5595     DPC
7573      HB
Name: source_code, dtype: object
```

on Destination column

In [31]:
```
df_aggid['destination_state'] = df_aggid['destination_name'].map(get_state)
df_aggid['destination_state'].head()
```

Out[31]:
```
0    Uttar Pradesh
1        Karnataka
2          Haryana
3      Maharashtra
4        Karnataka
Name: destination_state, dtype: object
```

In [32]:
```
df_aggid['destination_city'] = df_aggid['destination_name'].map(get_city)
df_aggid['destination_city'].head()
```

Out[32]:
```
0        Kanpur
1    Doddablpur
2       Gurgaon
3        Mumbai
4        Sandur
Name: destination_city, dtype: object
```

In [33]:
```
df_aggid['destination_place'] = df_aggid['destination_name'].map(get_place)
df_aggid['destination_place'].head()
```

Out[33]:
```
0     Central
1    ChikaDPP
2    Bilaspur
3      MiraRd
4    WrdN1DPP
Name: destination_place, dtype: object
```

In [34]:
```
df_aggid['destination_code'] = df_aggid['destination_name'].map(get_code)
df_aggid['destination_code'].head()
```

Out[34]:
```
0    H_6
1      D
2     HB
3     IP
4      D
Name: destination_code, dtype: object
```

In [35]:
```
df_aggid.head(5)
```

Out[35]:

	trip_uuid	source_center	destination_center	data	route_type	trip_creation_time	source_name	destinati
0	trip-153671041653548748	IND209304AAA	IND209304AAA	training	FTL	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	Kanpur_Cer (Uttar
1	trip-153671042288605164	IND561203AAB	IND561203AAB	training	Carting	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	Doddablpur_Chik (Ka
2	trip-153671043369099517	IND000000ACB	IND000000ACB	training	FTL	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)	Gurgaon_Bila (I
3	trip-153671046011330457	IND400072AAB	IND401104AAA	training	Carting	2018-09-12 00:01:00.113710	Mumbai Hub (Maharashtra)	Mumbai_M (Mah
4	trip-153671052974046625	IND583101AAA	IND583119AAA	training	FTL	2018-09-12 00:02:09.740725	Bellary_Dc (Karnataka)	Sandur_WrdN (Ka

5 rows × 25 columns

In [36]:
```
df_aggid['year'] = (df['trip_creation_time'].dt.year)
df_aggid['year'].head()
```

Out[36]:
```
0    2018.0
1    2018.0
2    2018.0
```

```
3    2018.0
4    2018.0
Name: year, dtype: float64
```

In [37]:
```python
df_aggid['month'] = df['trip_creation_time'].dt.month_name()
df_aggid['month'] .head()
```

Out[37]:
```
0    September
1    September
2    September
3    September
4    September
Name: month, dtype: object
```

In [38]:
```python
df_aggid['week'] =  df['trip_creation_time'].dt.isocalendar().week
df_aggid['week'].head()
```

Out[38]:
```
0    38
1    38
2    38
3    38
4    38
Name: week, dtype: UInt32
```

In [39]:
```python
df_aggid['day'] = (df['trip_creation_time'].dt.day).astype(int)
df_aggid['day'].head()
```

Out[39]:
```
0    20.0
1    20.0
2    20.0
3    20.0
4    20.0
Name: day, dtype: float64
```

In [40]:
```python
df_aggid['created_hour'] = df['trip_creation_time'].dt.hour
df_aggid['created_hour'].head()
```

Out[40]:
```
0    2.0
1    2.0
2    2.0
3    2.0
```

```
4    2.0
Name: created_hour, dtype: float64
```

In [41]:

```python
df_aggid.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14787 entries, 0 to 14786
Data columns (total 30 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   trip_uuid                       14787 non-null  object
 1   source_center                   14787 non-null  object
 2   destination_center              14787 non-null  object
 3   data                            14787 non-null  category
 4   route_type                      14787 non-null  category
 5   trip_creation_time              14787 non-null  datetime64[ns]
 6   source_name                     14787 non-null  object
 7   destination_name                14787 non-null  object
 8   od_total_time                   14787 non-null  float64
 9   start_scan_to_end_scan          14787 non-null  float64
 10  actual_distance_to_destination  14787 non-null  float64
 11  actual_time                     14787 non-null  float64
 12  osrm_time                       14787 non-null  float64
 13  osrm_distance                   14787 non-null  float64
 14  segment_actual_time             14787 non-null  float64
 15  segment_osrm_time               14787 non-null  float64
 16  segment_osrm_distance           14787 non-null  float64
 17  source_state                    14787 non-null  object
 18  source_city                     14787 non-null  object
 19  source_place                    12875 non-null  object
 20  source_code                     12875 non-null  object
 21  destination_state               14787 non-null  object
 22  destination_city                14787 non-null  object
 23  destination_place               12795 non-null  object
 24  destination_code                12795 non-null  object
 25  year                            14689 non-null  float64
 26  month                           14689 non-null  object
 27  week                            14689 non-null  UInt32
 28  day                             14689 non-null  float64
 29  created_hour                    14689 non-null  float64
```

```
dtypes: UInt32(1), category(2), datetime64[ns](1), float64(12), object(14)
memory usage: 3.1+ MB
```

In [42]:
```python
df_aggid['time_range'] = ((df ['od_end_time'] - df['od_start_time']).dt.total_seconds() / 3600).round(2)
```

In [43]:
```python
df.describe().T
```

Out[43]:

	count	mean	min	25%	50%	75%
trip_creation_time	144316	2018-09-22 13:05:09.454117120	2018-09-12 00:00:16.535741	2018-09-17 02:46:11.004421120	2018-09-22 03:36:19.186585088	2018-09-27 17:53:19.027942912
od_start_time	144316	2018-09-22 17:32:42.435769344	2018-09-12 00:00:16.535741	2018-09-17 07:37:35.014584832	2018-09-22 07:35:23.038482944	2018-09-27 22:01:30.861209088
od_end_time	144316	2018-09-23 09:36:54.057172224	2018-09-12 00:50:10.814399	2018-09-18 01:29:56.978912	2018-09-23 02:49:00.936600064	2018-09-28 12:13:41.675546112
start_scan_to_end_scan	144316.0	963.697698	20.0	161.0	451.0	1645.0
actual_distance_to_destination	144316.0	234.708498	9.000045	23.352027	66.135322	286.919294
actual_time	144316.0	417.996237	9.0	51.0	132.0	516.0
osrm_time	144316.0	214.437055	6.0	27.0	64.0	259.0
osrm_distance	144316.0	285.549785	9.0082	29.89625	78.6244	346.3054
segment_actual_time	144316.0	36.175379	-244.0	20.0	28.0	40.0
segment_osrm_time	144316.0	18.495697	0.0	11.0	17.0	22.0
segment_osrm_distance	144316.0	22.818993	0.0	12.053975	23.5083	27.813325

In [44]:
```python
df.describe(include='object').T
```

Out[44]:

	count	unique	top	freq

route_schedule_uuid	144316	1497	thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f...	1812
trip_uuid	144316	14787	trip-153837029526866991	101
source_center	144316	1496	IND000000ACB	23267
source_name	144316	1496	Gurgaon_Bilaspur_HB (Haryana)	23267
destination_center	144316	1466	IND000000ACB	15192
destination_name	144316	1466	Gurgaon_Bilaspur_HB (Haryana)	15192

Hypothesis Testing & Visual Analysis

Hypothesis Testing Frame Work

actual_time aggregated value and OSRM time aggregated value

Step 1: Set up Null Hypothesis

- **Null Hypothesis (HO):** The mean actual differnece between aggregated value and OSRM time aggregated value same
- **ALternative Hypothesis (HA):** The mean actual differnece between aggregated value and OSRM time aggregated value holds siginificance 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 : 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.

```
1. p-val > alpha : Accept H0
2. p-val < alpha : Reject H0
```

Creating custom Functions

In [45]:

```
def stats_desc(col1, col2):
    """Returns the statistical description of the specified columns in the dataset."""
    return df_aggid[[col1, col2]].describe().T
```

In [46]:

```
# plotting the Distributions for of the columns

def plot_dist(col1, col2):

    """Returns the hist plotting  of the specified columns in the dataset."""
```

```python
    try:
        plt.figure(figsize=(12, 6))
        # first plot
        plt.subplot(121)
        print(sns.histplot(df_aggid[col1], bins=100,element = 'step', color = 'green'))


        # Second Plot
        plt.subplot(122)
        print(sns.histplot(df_aggid[col2], bins=100,element = 'step', color = 'pink'))

        plt.tight_layout()
        plt.show()

    except Exception as e:
        print(f'The Error caused due to {e}')
```

In [47]:

```python
# Distribution check using QQ Plot
def qq_plot(col1, col2):
    """Returns the QQ plotting of the specified columns in the dataset."""

    try:
        plt.figure(figsize=(12, 6))
        plt.suptitle(f'QQ plots for {col1} and {col2}')

        # first plot
        plt.subplot(121)
        print(st.probplot(df_aggid[col1], plot = plt, dist = 'norm'))
        plt.title(f'QQ plot for {col1}')


        # Second Plot
        plt.subplot(122)
        print(st.probplot(df_aggid[col2], plot = plt, dist = 'norm'))
        plt.title(f'QQ plot for {col2}')

        plt.tight_layout()
        plt.show()
```

```
    except Exception as e:
        print(f'The Error caused due to {e}')
```

In [48]:
```
# Shapiro-Walik test for normality

def shapiro_test(col1, col2):
    """Performs the Shapiro-Wilk test for normality on a 200-row sample of the specified columns in the dataset."""

    sample1 = df_aggid[col1].sample(200)
    sample2 = df_aggid[col2].sample(200)

    #testing for col1
    t_stat, p_value = st.shapiro(sample1)
    print('p_value', p_value)
    if p_value < 0.05:
        rel1 = ('The sample does not follow normal distribution')
    else:
        rel1 = ('The sample follows normal distribution')

    # tetsing for col2
    t_stat, p_value = st.shapiro(sample2)
    print('p_value', p_value)
    if p_value < 0.05:
        rel2 = ('The sample does not follow normal distribution')
    else:
        rel2 = ('The sample follows normal distribution')
    return (rel1, rel2)
```

In [49]:
```
# Variance Test using Levene test

def levene_test(col1, col2):

    """Performs Levene’s test for equal variances on a sample of the specified columns in the dataset."""

    stat_val, p_value = st.levene(df_aggid[col1],df_aggid[col2])
    print('p_value', p_value)

    alpha = 0.05
    if p_value < alpha:
        rel = 'The samples do not have  Homogenous Variance'
```

```python
    else:
        rel = 'The samples have Homogenous Variance'
    return rel
```

Hypothesis testing/ Visual analysis between od_total_time and start_scan_to_end_scan

---

Step 1: Set up the Hypotheses

- **Null Hypothesis (H_0):**
  The mean difference between the od_total_time (aggregated) and start_scan_to_end_scan (aggregated) is **not significantly different** (i.e., the means are equal).

- **Alternative Hypothesis (H_1):**
  The mean difference between the od_total_time (aggregated) and start_scan_to_end_scan (aggregated) is **significantly different**.

Step 2: Check Assumptions for the Hypothesis Test

1. **Normality Check**

   - Use a **Q-Q Plot** to visually assess whether the differences follow a normal distribution.
   - Optionally confirm with a **Shapiro-Wilk Test**.

2. **Homogeneity of Variance**

   - Use **Levene's Test** to check if the variances between the two groups are equal.

Step 3: Choose the Appropriate Statistical Test

- If the assumptions of normality and equal variances are met:

    - Perform an **Independent Samples T-Test**.
- If assumptions are **violated**:
    - Use the **Mann-Whitney U Test**, the non-parametric alternative to the T-Test for independent samples.

Step 4: Set the Significance Level (α)

- Set **α = 0.05**

Step 5: Make a Decision Based on the p-value

- If **p-value > α** → **Fail to reject H_0** (no significant difference)
- If **p-value < α** → **Reject H_0** (significant difference exists)

In [50]:

```
#  ('od_total_time',  'start_scan_to_end_scan')
df_aggid[['od_total_time',  'start_scan_to_end_scan']].head()
```

Out[50]:

	od_total_time	start_scan_to_end_scan
0	2260.11	2259.0
1	181.61	180.0
2	3934.36	3933.0
3	100.49	100.0
4	718.34	717.0

In [51]:

```
stats_desc('od_total_time',  'start_scan_to_end_scan')
```

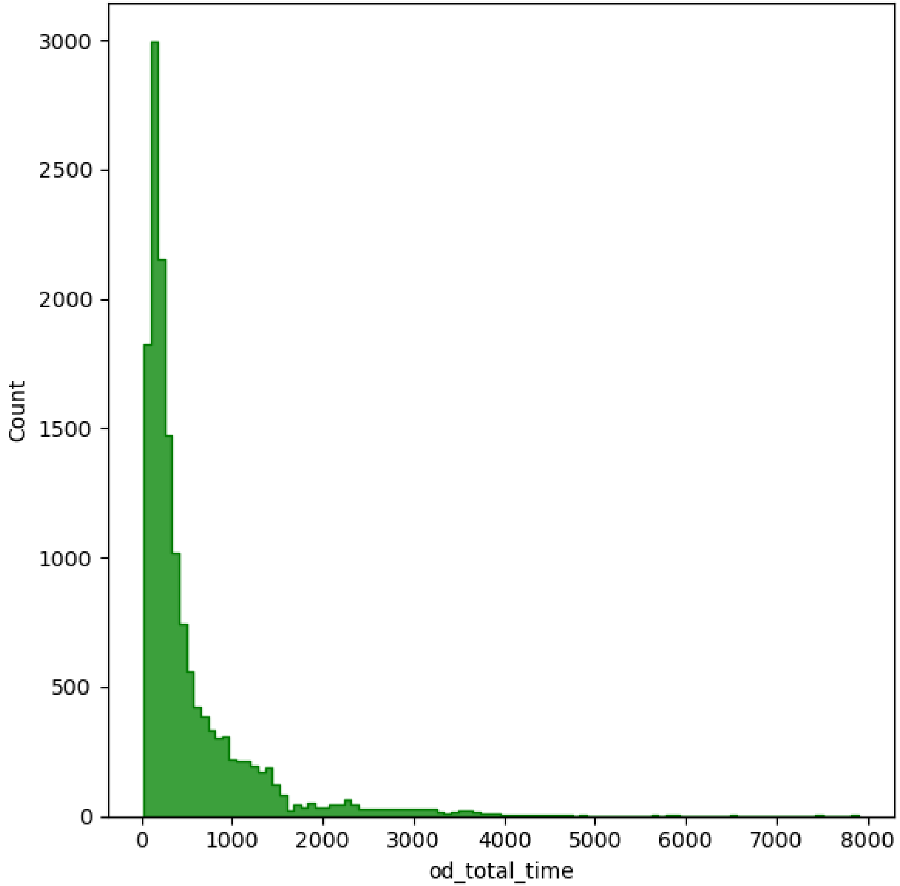
Out[51]:

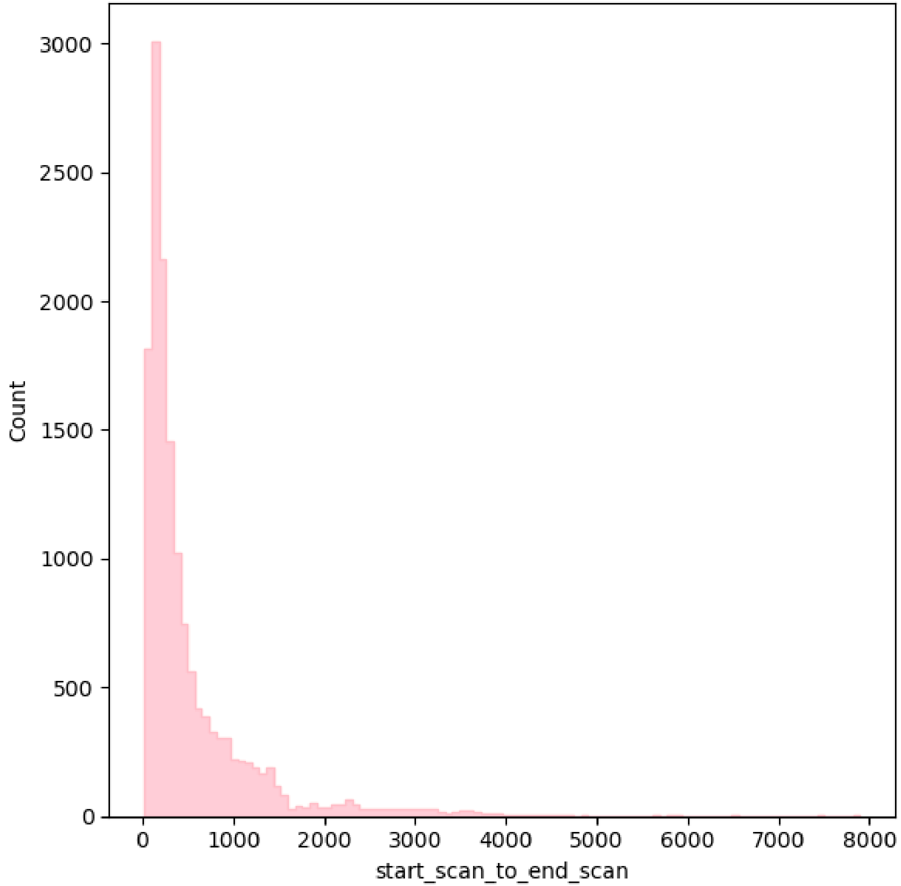
	count	mean	std	min	25%	50%	75%	max

od_total_time	14787.0	530.313468	658.415416	23.46	149.695	279.71	633.535	7898.55
start_scan_to_end_scan	14787.0	529.429025	658.254936	23.00	149.000	279.00	632.000	7898.00

In [52]:
```
plot_dist ('od_total_time',  'start_scan_to_end_scan')
```

```
Axes(0.125,0.11;0.352273x0.77)
Axes(0.547727,0.11;0.352273x0.77)
```

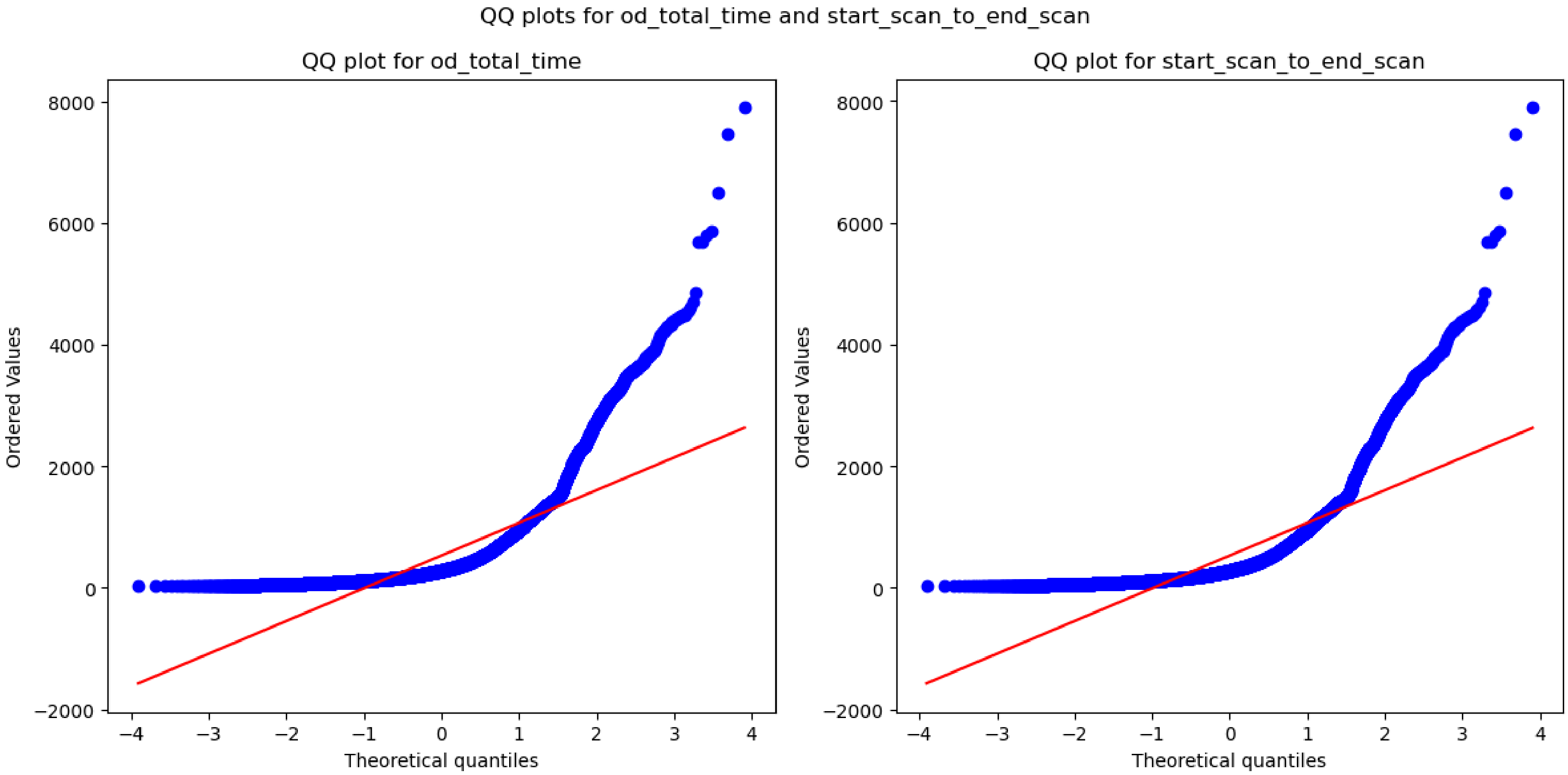




In [53]:
```
qq_plot('od_total_time',  'start_scan_to_end_scan')
```

```
((array([-3.90622638, -3.68627647, -3.56575533, ...,  3.56575533,
        3.68627647,  3.90622638]), array([  23.46,   26.5 ,   26.58, ..., 6496.02, 7458.94, 7898.55])), (537.9246290
```

```
768618, 530.3134679110028, 0.8168212377722497))
((array([-3.90622638, -3.68627647, -3.56575533, ...,  3.56575533,
       3.68627647,  3.90622638]), array([  23.,   26.,   26., ..., 6495., 7458., 7898.])), (537.6611256744281, 529.
4290254953675, 0.8166201568117032))
```



In [54]:
```
levene_test('od_total_time',  'start_scan_to_end_scan')
```

```
p_value 0.9671810468715469
```

Out[54]: 'The samples have Homogenous Variance'

In [55]:
```
shapiro_test ('od_total_time',  'start_scan_to_end_scan')
```

```
p_value 7.526206717878174e-19
p_value 7.264394651288022e-21
```

Out[55]:
```
('The sample does not follow normal distribution',
 'The sample does not follow normal distribution')
```

Conclusion from the Above Analysis

- **Histogram Plot**: Indicates that the data is **right-skewed**.
- **Q-Q Plot**: Deviations from the reference line suggest the data **does not follow a normal (Gaussian) distribution**.
- **Shapiro-Wilk Test**: The sample **does not follow a normal distribution** (p-value < 0.05).
- **Levene's Test**: The samples **do not have homogeneous variances** (p-value < 0.05).

Therefore:

Since the assumptions for an Independent Samples **T-Test** (normality and equal variances) are **not met**,
we cannot proceed with a parametric T-Test. Instead, a **non-parametric alternative such as the Mann-Whitney U Test** should be used.

In [56]:
```
# boxcox transformation
def boxcox_test(col1, col2):
    """Applies Box-Cox transformation to normalize the specified column(s) in the dataset."""

    # Apply Box-Cox to both columns
    transformed1 = st.boxcox(df_aggid[col1])[0]
    transformed2 = st.boxcox(df_aggid[col2])[0]

    # Convert to DataFrames with column names
    transformed1 = pd.DataFrame(transformed1, columns=[f"{col1}_boxcox"])
    transformed2 = pd.DataFrame(transformed2, columns=[f"{col2}_boxcox"])

    # Combine side by side
    return pd.concat([transformed1, transformed2], axis=1)
```

In [57]:
```
box_val  = boxcox_test('od_total_time',  'start_scan_to_end_scan')
box_val.head()
```

Out[57]:

od_total_time_boxcox	start_scan_to_end_scan_boxcox

0	4.720819	4.748396
1	3.695012	3.706278
2	4.901784	4.932104
3	3.397090	3.407413
4	4.298992	4.320408

In [58]:

```
# Shapiro-Wilk test for normality

def shapiro_test_tt(col1, col2):
    sample1 = box_val[col1].sample(200)
    sample2 = box_val[col2].sample(200)

    #testing for col1
    t_stat, p_value = st.shapiro(sample1)
    if p_value < 0.05:
        rel1 = ('The sample does not follow normal distribution')
    else:
        rel1 = ('The sample follows normal distribution')

    # tetsing for col2
    t_stat, p_value = st.shapiro(sample2)
    if p_value < 0.05:
        rel2 = ('The sample does not follow normal distribution')
    else:
        rel2 = ('The sample follows normal distribution')
    return (rel1, rel2)
```

In [59]:

```
shapiro_test_tt('od_total_time_boxcox',  'start_scan_to_end_scan_boxcox')
```

Out[59]:

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

In [60]:

```
test_stat, p_value = st.mannwhitneyu(df_aggid['od_total_time'], df_aggid['start_scan_to_end_scan'])
print('P-value :',p_value)
if p_value < 0.05:
```

```
    print('Samples are significantly different')
else:
    print('Samples are not significantly different')
```

```
P-value : 0.780940379505003
Samples are not significantly different
```

Since the p-value is greater than the significance level (α), we fail to reject the null hypothesis. Therefore, it can be concluded that od_total_time and start_scan_to_end_scan are statistically similar.

Hypothesis testing/ visual analysis between actual_time aggregated value and OSRM time aggregated value

Step 1: Set up the Hypotheses

- **Null Hypothesis (H_0):**
  The mean difference between the actual time (aggregated) and OSRM time (aggregated) is **not significantly different** (i.e., the means are equal).

- **Alternative Hypothesis (H_1):**
  The mean difference between the actual time (aggregated) and OSRM time (aggregated) is **significantly different**.

Step 2: Check Assumptions for the Hypothesis Test

1. **Normality Check**

   - Use a **Q-Q Plot** to visually assess whether the differences follow a normal distribution.
   - Optionally confirm with a **Shapiro-Wilk Test**.
2. **Homogeneity of Variance**

- Use **Levene's Test** to check if the variances between the two groups are equal.

Step 3: Choose the Appropriate Statistical Test

- If the assumptions of normality and equal variances are met:
  - Perform an **Independent Samples T-Test**.
- If assumptions are **violated**:
  - Use the **Mann-Whitney U Test**, the non-parametric alternative to the T-Test for independent samples.

Step 4: Set the Significance Level (α)

- Set **α = 0.05**

Step 5: Make a Decision Based on the p-value

- If **p-value > α** → **Fail to reject H_0** (no significant difference)
- If **p-value < α** → **Reject H_0** (significant difference exists)

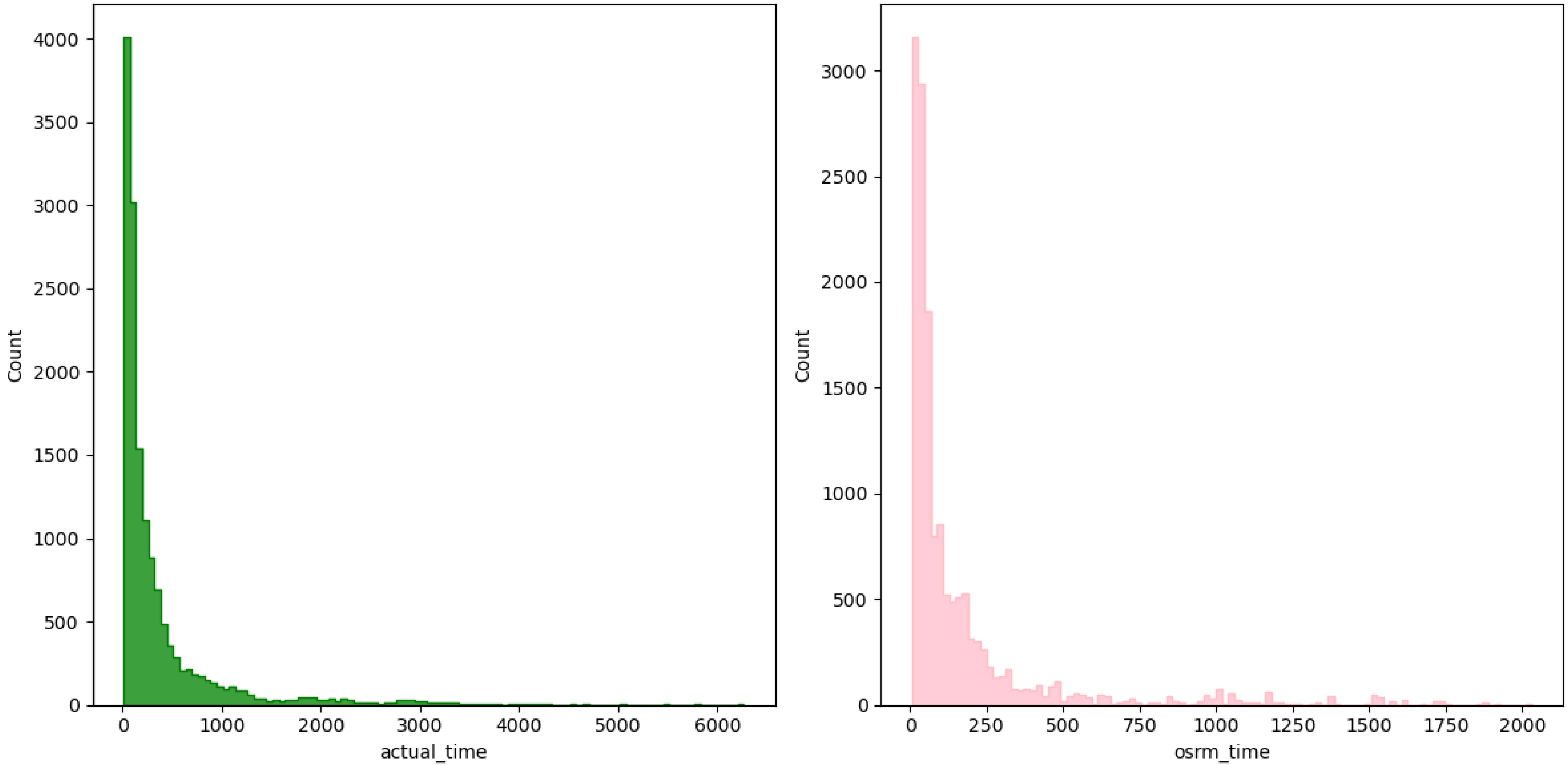
In [61]:
```
stats_desc('actual_time', 'osrm_time')
```

Out[61]:

	count	mean	std	min	25%	50%	75%	max
actual_time	14787.0	356.306012	561.517936	9.0	67.0	148.0	367.0	6265.0
osrm_time	14787.0	160.990938	271.459495	6.0	29.0	60.0	168.0	2032.0

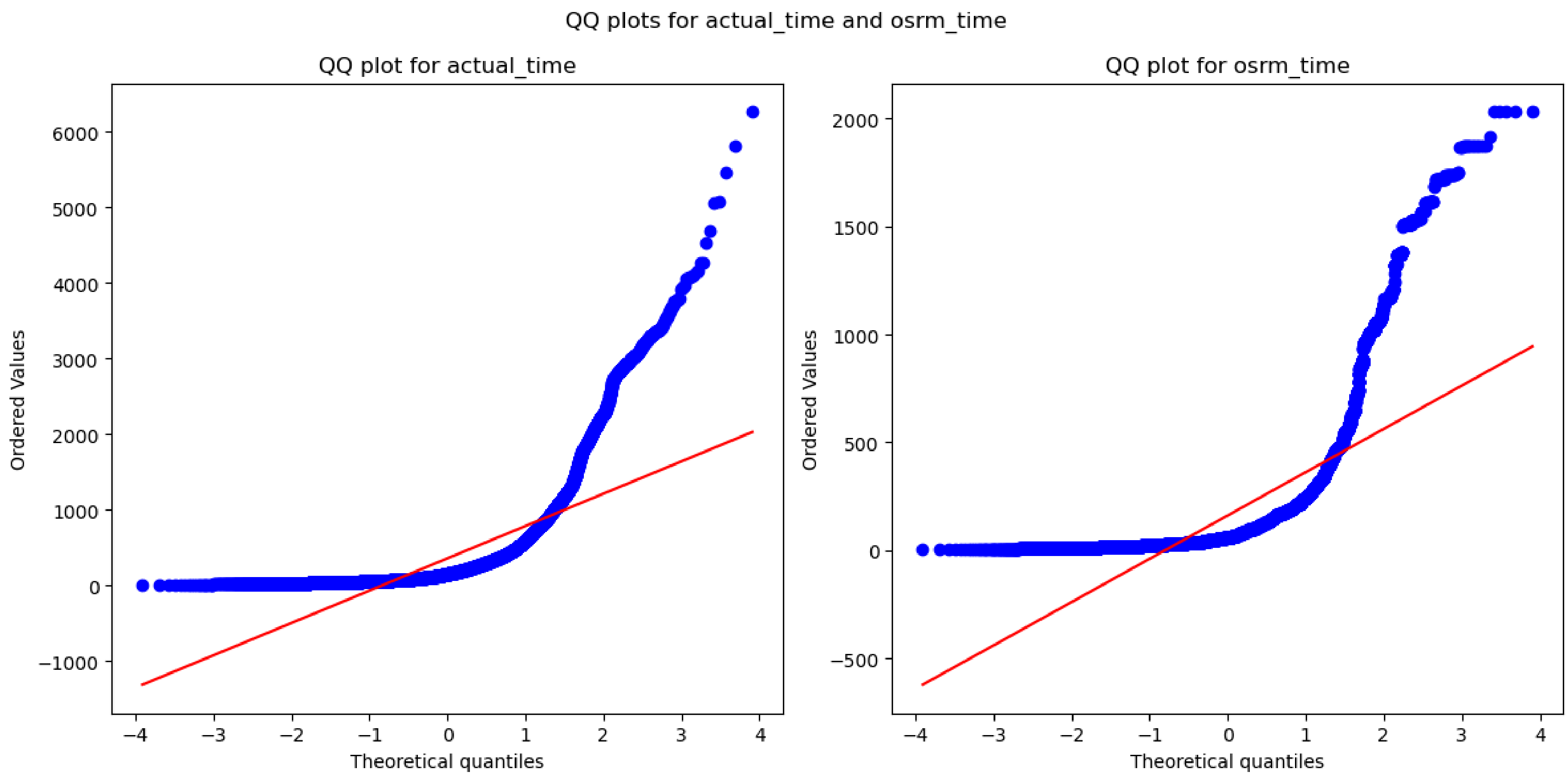
In [62]:
```
plot_dist('actual_time', 'osrm_time')
```

```
Axes(0.125,0.11;0.352273x0.77)
Axes(0.547727,0.11;0.352273x0.77)
```



In [63]:
```
qq_plot('actual_time', 'osrm_time')
```

```
((array([-3.90622638, -3.68627647, -3.56575533, ...,  3.56575533,
        3.68627647,  3.90622638]), array([   9.,    9.,   10., ..., 5465., 5804., 6265.])), (427.79748769756117, 35
6.30601203760045, 0.761693377848543))
((array([-3.90622638, -3.68627647, -3.56575533, ...,  3.56575533,
        3.68627647,  3.90622638]), array([   6.,    7.,    7., ..., 2031., 2032., 2032.])), (200.5670444872438, 160.
9909379860688, 0.7386864311178046))
```



In [64]:
```
shapiro_test('actual_time', 'osrm_time')
```

```
p_value 2.421566794073483e-23
p_value 1.103883634613561e-21
```

Out[64]:
```
('The sample does not follow normal distribution',
 'The sample does not follow normal distribution')
```

In [65]:
```
levene_test('actual_time', 'osrm_time')
```

```
p_value 8.743536461316657e-219
```

Out[65]:
```
'The samples do not have  Homogenous Variance'
```

Conclusion from the Above Analysis

- **Histogram Plot**: Indicates that the data is **right-skewed**.
- **Q-Q Plot**: Deviations from the reference line suggest the data **does not follow a normal (Gaussian) distribution**.
- **Shapiro-Wilk Test**: The sample **does not follow a normal distribution** (p-value < 0.05).
- **Levene's Test**: The samples **do not have homogeneous variances** (p-value < 0.05).

Therefore:

Since the assumptions for an Independent Samples **T-Test** (normality and equal variances) are **not met**,
we cannot proceed with a parametric T-Test. Instead, a **non-parametric alternative such as the Mann-Whitney U Test** should be used.

In [66]:
```
# boxcox transformation
def boxcox_test(col1, col2):
    """Applies Box-Cox transformation to normalize the specified column(s) in the dataset."""

    # Apply Box-Cox to both columns
    transformed1 = st.boxcox(df_aggid[col1])[0]
    transformed2 = st.boxcox(df_aggid[col2])[0]

    # Convert to DataFrames with column names
    transformed1 = pd.DataFrame(transformed1, columns=[f"{col1}_boxcox"])
    transformed2 = pd.DataFrame(transformed2, columns=[f"{col2}_boxcox"])

    # Combine side by side
    return pd.concat([transformed1, transformed2], axis=1)
```

In [67]:
```
boxcox_values = boxcox_test('actual_time', 'osrm_time')
boxcox_values.head()
```

Out[67]:

	actual_time_boxcox	osrm_time_boxcox
0	4.363873	3.520374
1	3.448421	2.774050

2	4.590560	3.716826
3	3.012351	2.052965
4	3.821448	2.980870

In [68]:
```
# Shapiro-Wilk test for normality

def shapiro_test1(col1, col2):
    sample1 = boxcox_values[col1].sample(200)
    sample2 = boxcox_values[col2].sample(200)

    #testing for col1
    t_stat, p_value = st.shapiro(sample1)
    if p_value < 0.05:
        rel1 = ('The sample does not follow normal distribution')
    else:
        rel1 = ('The sample follows normal distribution')

    # tetsing for col2
    t_stat, p_value = st.shapiro(sample2)
    if p_value < 0.05:
        rel2 = ('The sample does not follow normal distribution')
    else:
        rel2 = ('The sample follows normal distribution')
    return (rel1, rel2)
```

In [69]:
```
shapiro_test1('actual_time_boxcox', 'osrm_time_boxcox')
```

Out[69]:
```
('The sample follows normal distribution',
 'The sample does not follow normal distribution')
```

Since the samples violate the assumptions required for a T-Test (normality and homogeneity of variances), it is not appropriate to use a parametric test in this case. Therefore, we proceed with the non-parametric alternative — the Mann-Whitney U Rank Test — for comparing two independent samples.

In [70]:
```
t_stat, p_value = st.mannwhitneyu(df_aggid['actual_time'], df_aggid['osrm_time'])
print('p-value', p_value)
if p_value < 0.05:
    print('Samples are significantly different')
else:
    print('Samples are not significantly different')
```

```
p-value 0.0
Samples are significantly different
```

Hypothesis testing/ visual analysis between actual_time aggregated value and segment actual time aggregated value

---

Step 1: Set up the Hypotheses

- **Null Hypothesis (H_0):**
  The mean difference between the actual time (aggregated) and segment actual time (aggregated) is **not significantly different** (i.e., the means are equal).

- **Alternative Hypothesis (H_1):**
  The mean difference between the actual time (aggregated) and segment actual time (aggregated) is **significantly different**.

Step 2: Check Assumptions for the Hypothesis Test

1. **Normality Check**
   - Use a **Q-Q Plot** to visually assess whether the differences follow a normal distribution.
   - Optionally confirm with a **Shapiro-Wilk Test**.
2. **Homogeneity of Variance**
   - Use **Levene's Test** to check if the variances between the two groups are equal.

Step 3: Choose the Appropriate Statistical Test

- If the assumptions of normality and equal variances are met:
  - Perform an **Independent Samples T-Test**.
- If assumptions are **violated**:
  - Use the **Mann-Whitney U Test**, the non-parametric alternative to the T-Test for independent samples.

Step 4: Set the Significance Level (α)

- Set **α = 0.05**

Step 5: Make a Decision Based on the p-value

- If **p-value > α** → **Fail to reject H_0** (no significant difference)
- If **p-value < α** → **Reject H_0** (significant difference exists)

In [71]:
```
df_aggid[['trip_uuid','actual_time', 'segment_actual_time']].head()
```

Out[71]:

	trip_uuid	actual_time	segment_actual_time
0	trip-153671041653548748	1562.0	1548.0
1	trip-153671042288605164	143.0	141.0
2	trip-153671043369099517	3347.0	3308.0
3	trip-153671046011330457	59.0	59.0
4	trip-153671052974046625	341.0	340.0

In [72]:
```
stats_desc('actual_time', 'segment_actual_time')
```

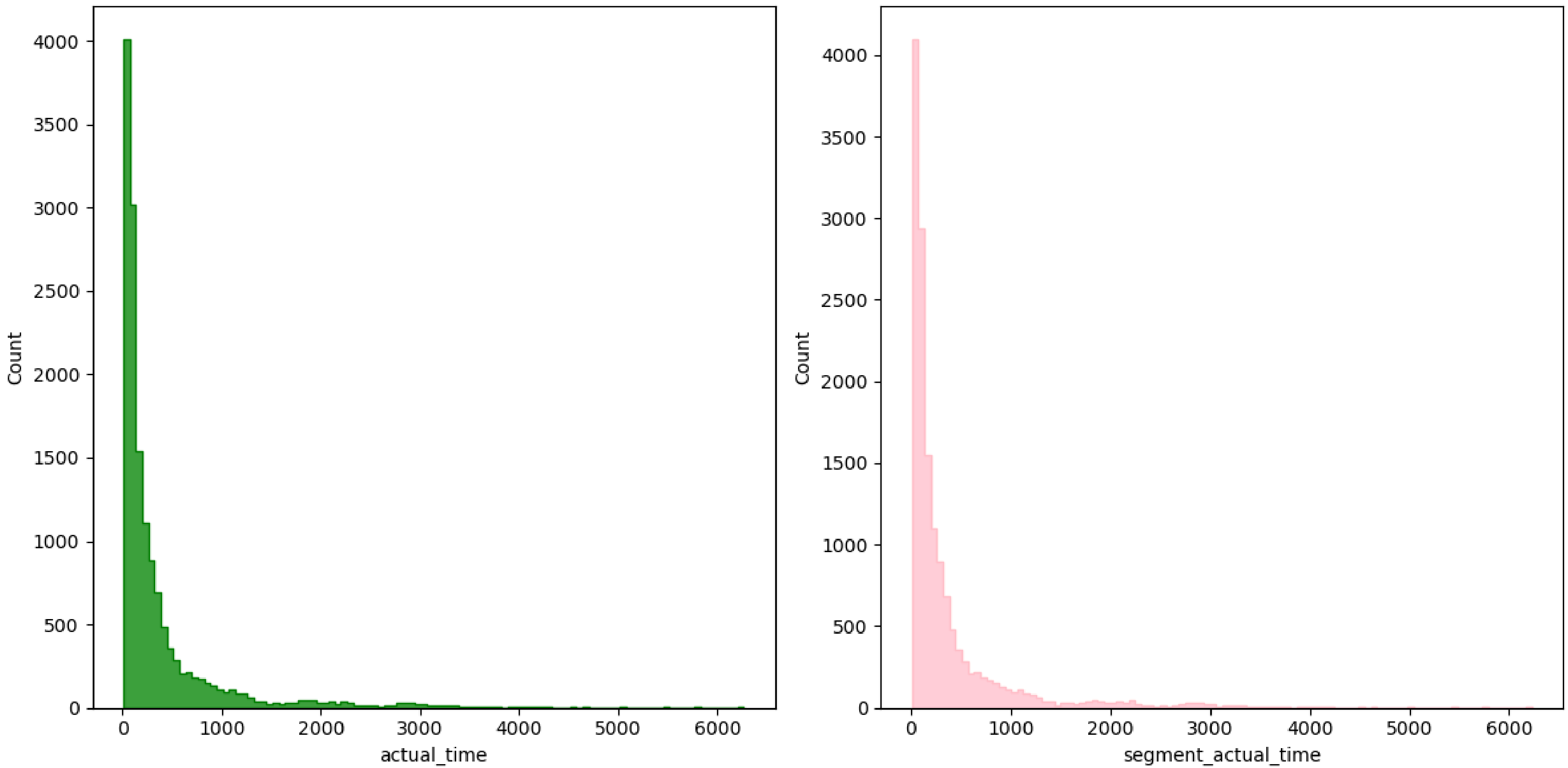
Out[72]:

	count	mean	std	min	25%	50%	75%	max
actual_time	14787.0	356.306012	561.517936	9.0	67.0	148.0	367.0	6265.0
segment_actual_time	14787.0	353.059174	556.365911	9.0	66.0	147.0	364.0	6230.0

In [73]:

```
plot_dist('actual_time', 'segment_actual_time')
```

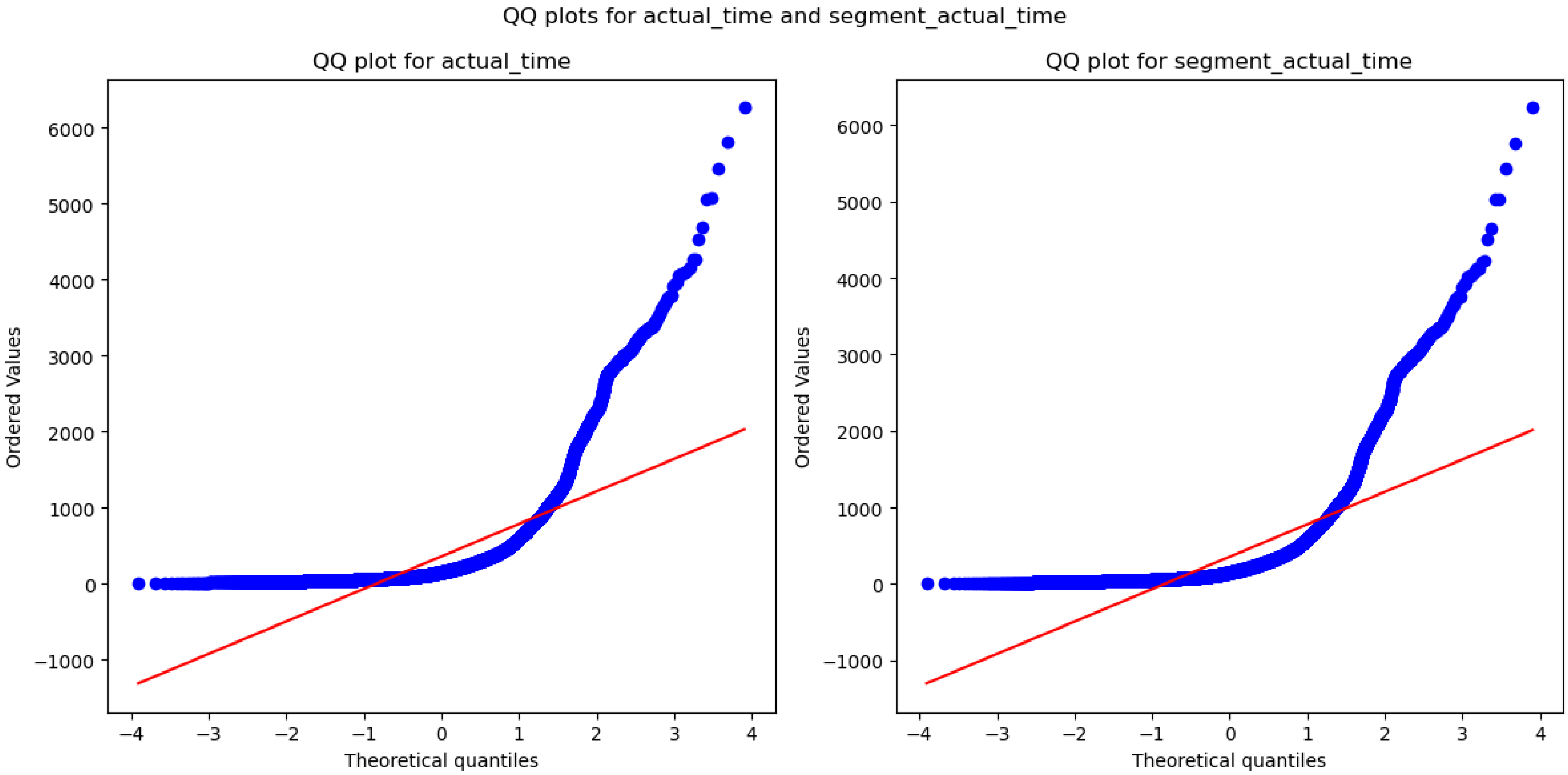
```
Axes(0.125,0.11;0.352273x0.77)
Axes(0.547727,0.11;0.352273x0.77)
```



In [74]:

```
qq_plot('actual_time', 'segment_actual_time')
```

```
((array([-3.90622638, -3.68627647, -3.56575533, ...,  3.56575533,
         3.68627647,  3.90622638]), array([   9.,     9.,    10., ..., 5465., 5804., 6265.])), (427.79748769756117, 35
6.30601203760045, 0.761693377848543))
((array([-3.90622638, -3.68627647, -3.56575533, ...,  3.56575533,
         3.68627647,  3.90622638]), array([   9.,     9.,    10., ..., 5427., 5768., 6230.])), (424.0536025033646, 353.
05917359843096, 0.7620190480749739))
```



In [75]:
```
levene_test('actual_time', 'segment_actual_time')
```

```
p_value 0.6962681452003544
```

Out[75]: 'The samples have Homogenous Variance'

In [76]:
```
shapiro_test('actual_time', 'segment_actual_time')
```

```
p_value 8.455841694919821e-23
p_value 3.500939756744471e-21
```

Out[76]:
```
('The sample does not follow normal distribution',
 'The sample does not follow normal distribution')
```

Conclusion from the Above Analysis

- **Histogram Plot**: Indicates that the data is **right-skewed**.
- **Q-Q Plot**: Deviations from the reference line suggest the data **does not follow a normal (Gaussian) distribution**.
- **Shapiro-Wilk Test**: The sample **does not follow a normal distribution** (p-value < 0.05).
- **Levene's Test**: The samples **do not have homogeneous variances** (p-value < 0.05).

Therefore:

Since the assumptions for an Independent Samples **T-Test** (normality and equal variances) are **not met**,
we cannot proceed with a parametric T-Test. Instead, a **non-parametric alternative such as the Mann-Whitney U Test** should be used.

In [77]:
```
boxcox_values2 = boxcox_test('actual_time', 'segment_actual_time')
boxcox_values2.head()
```

Out[77]:

	actual_time_boxcox	segment_actual_time_boxcox
0	4.363873	4.358946
1	3.448421	3.440757
2	4.590560	4.584911
3	3.012351	3.011471
4	3.821448	3.818755

In [78]:
```python
# Shapiro-Wilk test for normality

def shapiro_test2(col1, col2):

    '''Performs the Shapiro-Wilk test for normality on a sample of the specified columns in the dataset. '''

    sample1 = boxcox_values2[col1].sample(200)
    sample2 = boxcox_values2[col2].sample(200)

    #testing for col1
    t_stat, p_value = st.shapiro(sample1)
    print('p_value', p_value)
    if p_value < 0.05:
        rel1 = ('The sample does not follow normal distribution')
    else:
        rel1 = ('The sample follows normal distribution')

    # tetsing for col2
    t_stat, p_value = st.shapiro(sample2)
    print('p_value', p_value)
    if p_value < 0.05:
        rel2 = ('The sample does not follow normal distribution')
    else:
        rel2 = ('The sample follows normal distribution')
    return (rel1, rel2)
```

In [79]:
```python
shapiro_test2('actual_time_boxcox','segment_actual_time_boxcox')
```

```
p_value 0.1375802755355835
p_value 0.10669463127851486
```

Out[79]:
```
('The sample follows normal distribution',
 'The sample follows normal distribution')
```

Conclusion from the Above Analysis

- **Histogram Plot**: Indicates that the data is **right-skewed**.
- **Q-Q Plot**: Deviations from the reference line suggest the data **does not follow a normal (Gaussian) distribution**.

- **Shapiro-Wilk Test**: The sample **does not follow a normal distribution** (p-value < 0.05).
- **Levene's Test**: The samples **do not have homogeneous variances** (p-value < 0.05).

Therefore:

Since the assumptions for an Independent Samples **T-Test** (normality and equal variances) are **not met**,
we cannot proceed with a parametric T-Test. Instead, a **non-parametric alternative such as the Mann-Whitney U Test** should be used.

In [80]:
```
t_stat, p_value = st.mannwhitneyu(df_aggid['actual_time'], df_aggid['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 0.41578601931625214
The samples are similar
```

Since the p-value is less than the significance level (α = 0.05), we reject the null hypothesis. Therefore, it can be concluded that `actual_time` and `segment actual time` are not statistically similar. This suggests a significant difference in the distributions of these two variables, indicating potential discrepancies between the total OSRM distance and the sum of segment-level OSRM distances.

Hypothesis testing/ visual analysis between osrm distance aggregated value and segment osrm distance aggregated value

---

Step 1: Set up the Hypotheses

- **Null Hypothesis (H_0):**
  The mean difference between the osrm distance (aggregated) and segment osrm distance (aggregated) is **not significantly different**

(i.e., the means are equal).

- **Alternative Hypothesis (H_1):**
  The mean difference between the osrm distance (aggregated) and segment osrm distance (aggregated) is **significantly different**.

Step 2: Check Assumptions for the Hypothesis Test

1. **Normality Check**

   - Use a **Q-Q Plot** to visually assess whether the differences follow a normal distribution.
   - Optionally confirm with a **Shapiro-Wilk Test**.

2. **Homogeneity of Variance**

   - Use **Levene’s Test** to check if the variances between the two groups are equal.

Step 3: Choose the Appropriate Statistical Test

- If the assumptions of normality and equal variances are met:
  - Perform an **Independent Samples T-Test**.
- If assumptions are **violated**:
  - Use the **Mann-Whitney U Test**, the non-parametric alternative to the T-Test for independent samples.

Step 4: Set the Significance Level (α)

- Set **$\alpha = 0.05$**

Step 5: Make a Decision Based on the p-value

- If **p-value > α** → **Fail to reject H_0** (no significant difference)
- If **p-value < α** → **Reject H_0** (significant difference exists)

In [81]:
```python
# ('osrm_distance', 'segment_osrm_distance')
df_aggid[['osrm_distance', 'segment_osrm_distance']].head()
```

Out[81]:

	osrm_distance	segment_osrm_distance
0	991.3523	1320.4733
1	85.1110	84.1894
2	2354.0665	2545.2678
3	19.6800	19.8766
4	146.7918	146.7919

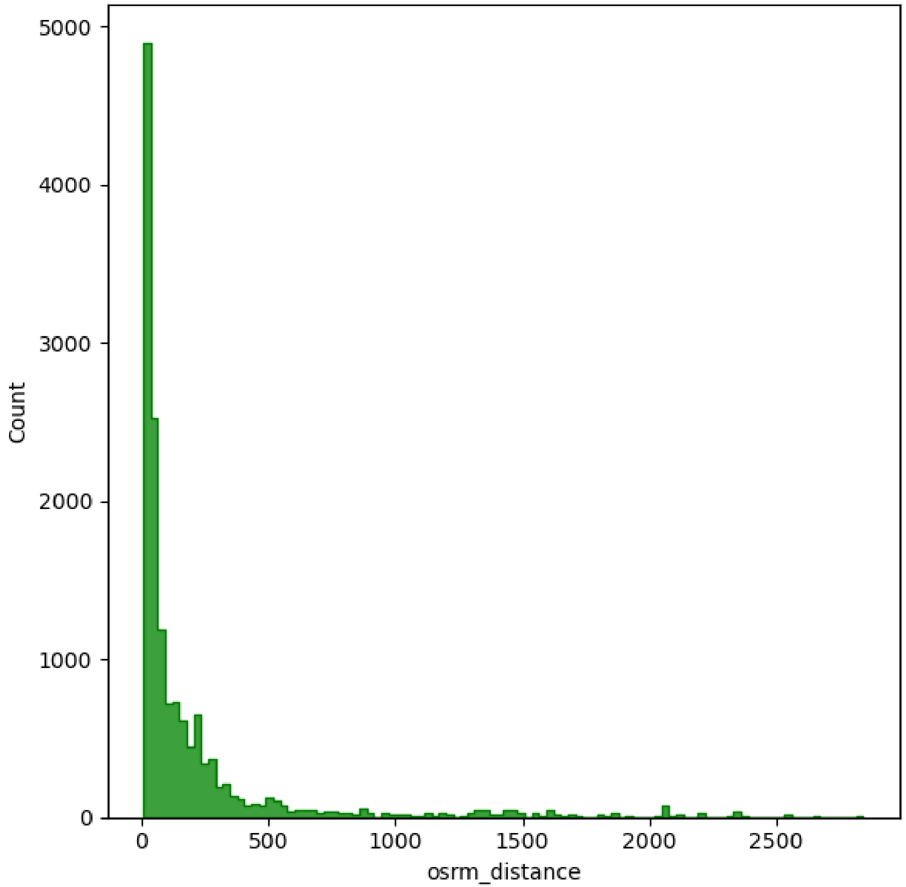
In [82]:
```python
stats_desc('osrm_distance', 'segment_osrm_distance')
```

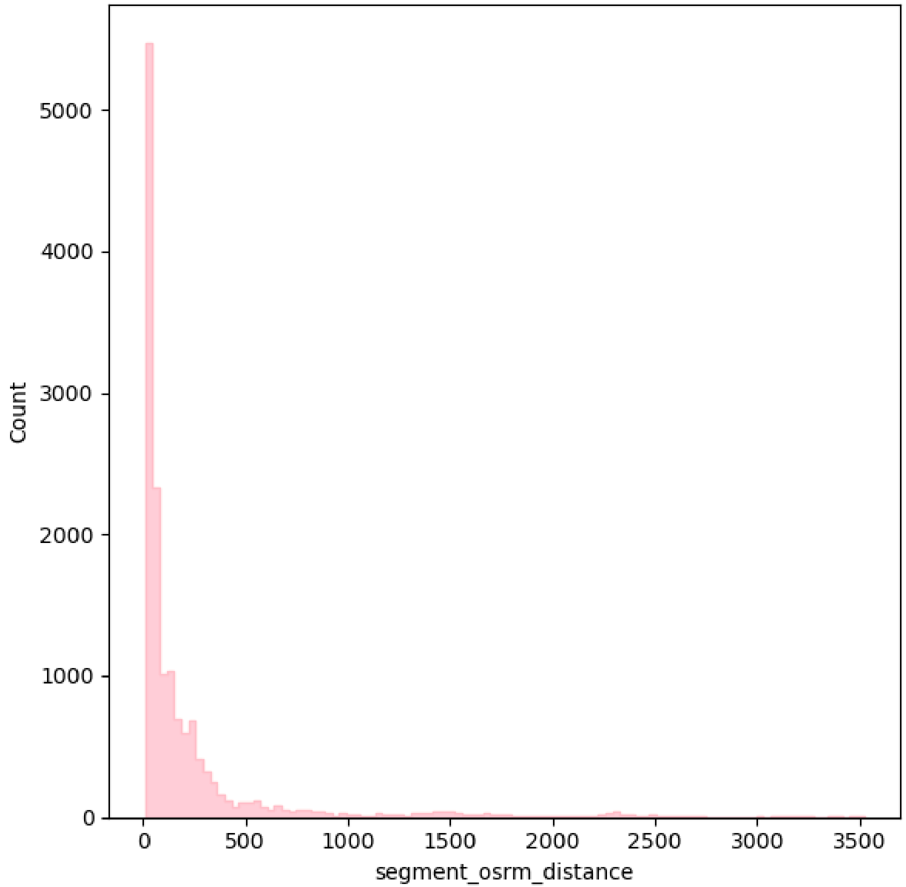
Out[82]:

	count	mean	std	min	25%	50%	75%	max
osrm_distance	14787.0	203.887411	370.565564	9.0729	30.75690	65.3028	206.6442	2840.0810
segment_osrm_distance	14787.0	222.705466	416.846279	9.0729	32.57885	69.7842	216.5606	3523.6324

In [83]:
```python
plot_dist('osrm_distance', 'segment_osrm_distance')
```

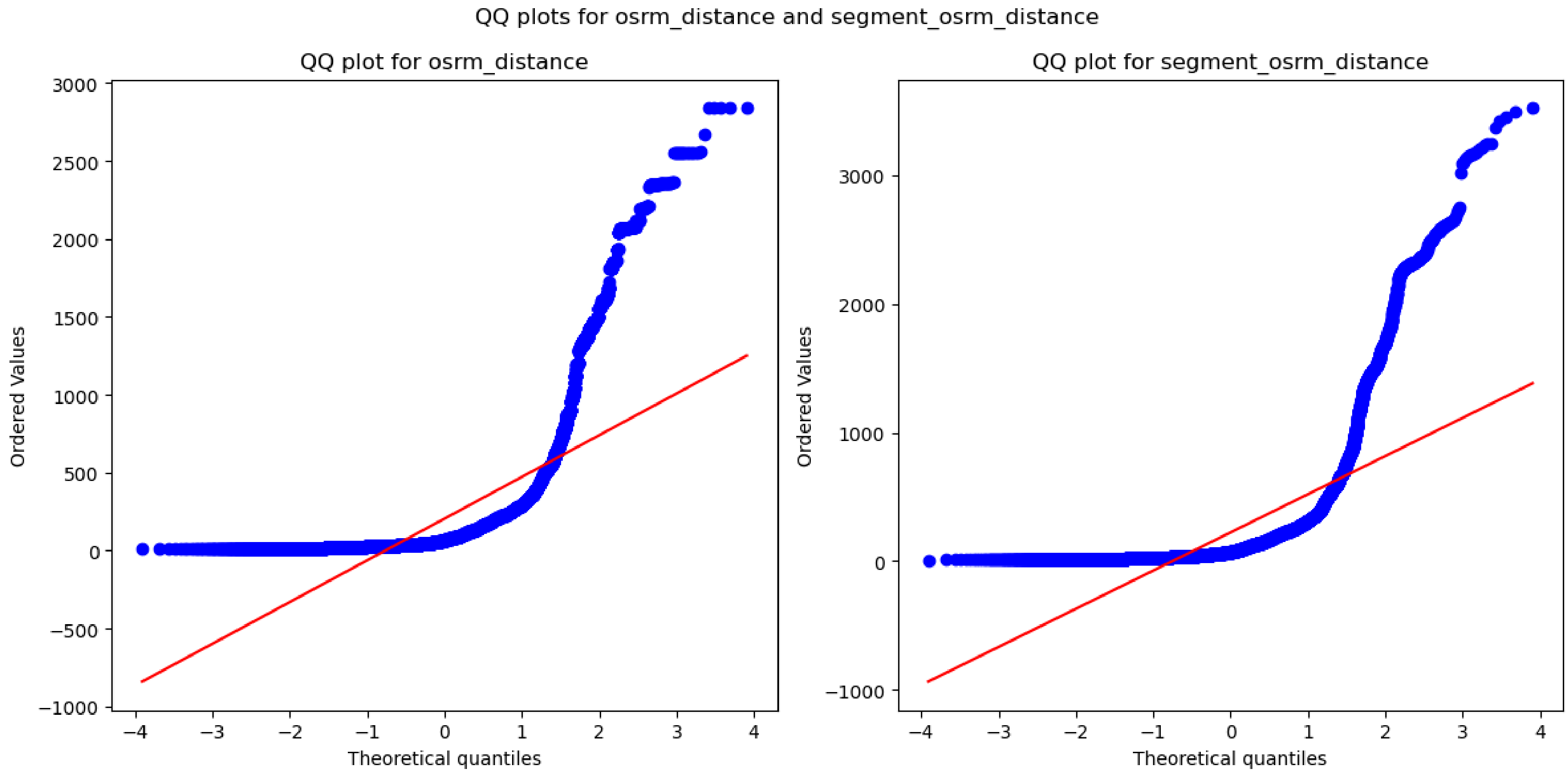
```
Axes(0.125,0.11;0.352273x0.77)
Axes(0.547727,0.11;0.352273x0.77)
```





In [84]:
```
qq_plot('osrm_distance', 'segment_osrm_distance')
```

```
((array([-3.90622638, -3.68627647, -3.56575533, ...,  3.56575533,
         3.68627647,  3.90622638]), array([   9.0729,    9.1364,    9.2903, ..., 2839.3582, 2839.6603,
       2840.081 ])), (267.6806180557242, 203.88741124636493, 0.7221999437884683))
((array([-3.90622638, -3.68627647, -3.56575533, ...,  3.56575533,
         3.68627647,  3.90622638]), array([   9.0729,    9.1364,    9.2903, ..., 3456.0357, 3489.9866,
       3523.6324])), (296.8831021430198, 222.70546644349756, 0.7120576112855832))
```



In [85]:
```
shapiro_test('osrm_distance', 'segment_osrm_distance')
```

```
p_value 7.153291292070077e-24
p_value 9.035737448424494e-24
```

Out[85]:
```
('The sample does not follow normal distribution',
 'The sample does not follow normal distribution')
```

In [86]:
```
boxcox_values3 = boxcox_test('osrm_distance', 'segment_osrm_distance')
boxcox_values3.head()
```

Out[86]:

osrm_distance_boxcox	segment_osrm_distance_boxcox

0	3.469969	3.658440
1	2.790050	2.857677
2	3.631950	3.788956
3	2.160524	2.205227
4	2.975521	3.059653

In [87]:

```
# Shapiro-Wilk test for normality

def shapiro_test3(col1, col2):
    sample1 = boxcox_values3[col1].sample(200)
    sample2 = boxcox_values3[col2].sample(200)

    #testing for col1
    t_stat, p_value = st.shapiro(sample1)
    print('p_value', p_value)
    if p_value < 0.05:
        rel1 = ('The sample does not follow normal distribution')
    else:
        rel1 = ('The sample follows normal distribution')

    # tetsing for col2
    t_stat, p_value = st.shapiro(sample2)
    print('p_value', p_value)
    if p_value < 0.05:
        rel2 = ('The sample does not follow normal distribution')
    else:
        rel2 = ('The sample follows normal distribution')
    return (rel1, rel2)
```

In [88]:

```
shapiro_test3('osrm_distance_boxcox','segment_osrm_distance_boxcox')
```

```
p_value 0.003435838967561722
p_value 0.0006328711169771 85
```

Out[88]:

```
('The sample does not follow normal distribution',
 'The sample does not follow normal distribution')
```

In [89]:
```
levene_test('osrm_distance', 'segment_osrm_distance')
```

```
p_value 0.00022171213513990103
```

Out[89]:
```
'The samples do not have  Homogenous Variance'
```

Conclusion from the Above Analysis

- **Histogram Plot**: Indicates that the data is **right-skewed**.
- **Q-Q Plot**: Deviations from the reference line suggest the data **does not follow a normal (Gaussian) distribution**.
- **Shapiro-Wilk Test**: The sample **does not follow a normal distribution** (p-value < 0.05).
- **Levene's Test**: The samples **do not have homogeneous variances** (p-value < 0.05).

Therefore:

Since the assumptions for an Independent Samples **T-Test** (normality and equal variances) are **not met**,
we cannot proceed with a parametric T-Test. Instead, a **non-parametric alternative such as the Mann-Whitney U Test** should be used.

In [90]:
```
t_stat, p_value = st.mannwhitneyu(df_aggid['osrm_distance'], df_aggid['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 1.0001087659092072e-06
The samples are not similar
```

Since the p-value is less than the significance level (α), we reject the null hypothesis. Therefore, it can be concluded that `osrm_distance` and `segment_osrm_distance` are not statistically similar.

Hypothesis testing/ visual analysis between osrm time aggregated value and segment osrm time aggregated value

---

Step 1: Set up the Hypotheses

- **Null Hypothesis (H_0):**
  The mean difference between the osrm time (aggregated) and segment osrm time (aggregated) is **not significantly different** (i.e., the means are equal).

- **Alternative Hypothesis (H_1):**
  The mean difference between the osrm time (aggregated) and segment osrm time (aggregated) is **significantly different.**

Step 2: Check Assumptions for the Hypothesis Test

1. **Normality Check**

   - Use a **Q-Q Plot** to visually assess whether the differences follow a normal distribution.
   - Optionally confirm with a **Shapiro-Wilk Test**.
2. **Homogeneity of Variance**

   - Use **Levene's Test** to check if the variances between the two groups are equal.

Step 3: Choose the Appropriate Statistical Test

- If the assumptions of normality and equal variances are met:
  - Perform an **Independent Samples T-Test**.
- If assumptions are **violated**:
  - Use the **Mann-Whitney U Test**, the non-parametric alternative to the T-Test for independent samples.

Step 4: Set the Significance Level (α)

- Set **α = 0.05**

Step 5: Make a Decision Based on the p-value

- If **p-value > α** → **Fail to reject H_0** (no significant difference)
- If **p-value < α** → **Reject H_0** (significant difference exists)

In [91]:
```
#  ('osrm_time', 'segment_osrm_time')
df_aggid[['osrm_time', 'segment_osrm_time']].head()
```

Out[91]:

	osrm_time	segment_osrm_time
0	717.0	1008.0
1	68.0	65.0
2	1740.0	1941.0
3	15.0	16.0
4	117.0	115.0

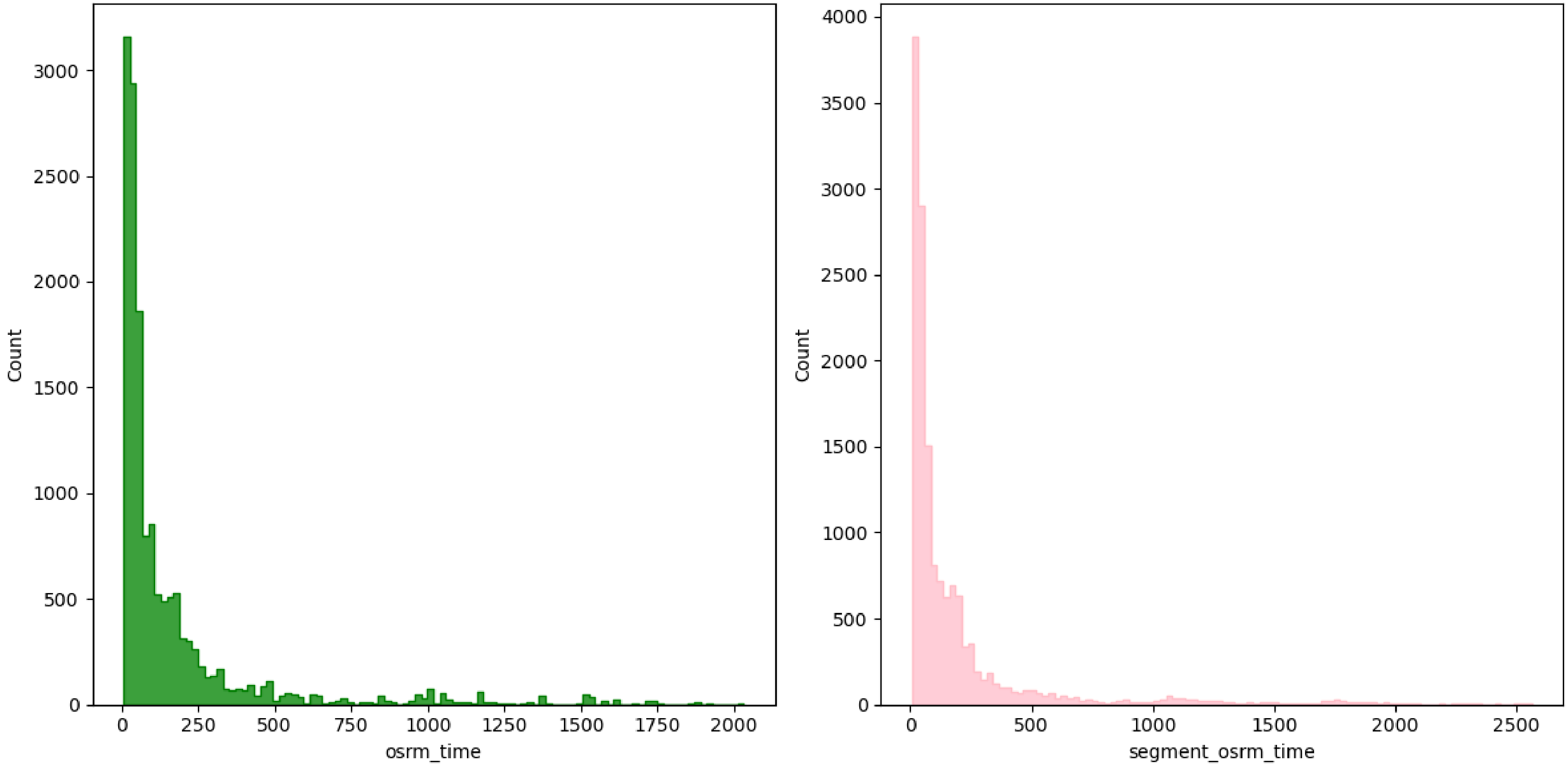
In [92]:
```
stats_desc('osrm_time', 'segment_osrm_time')
```

Out[92]:

	count	mean	std	min	25%	50%	75%	max
osrm_time	14787.0	160.990938	271.459495	6.0	29.0	60.0	168.0	2032.0
segment_osrm_time	14787.0	180.511598	314.679279	6.0	30.0	65.0	184.0	2564.0

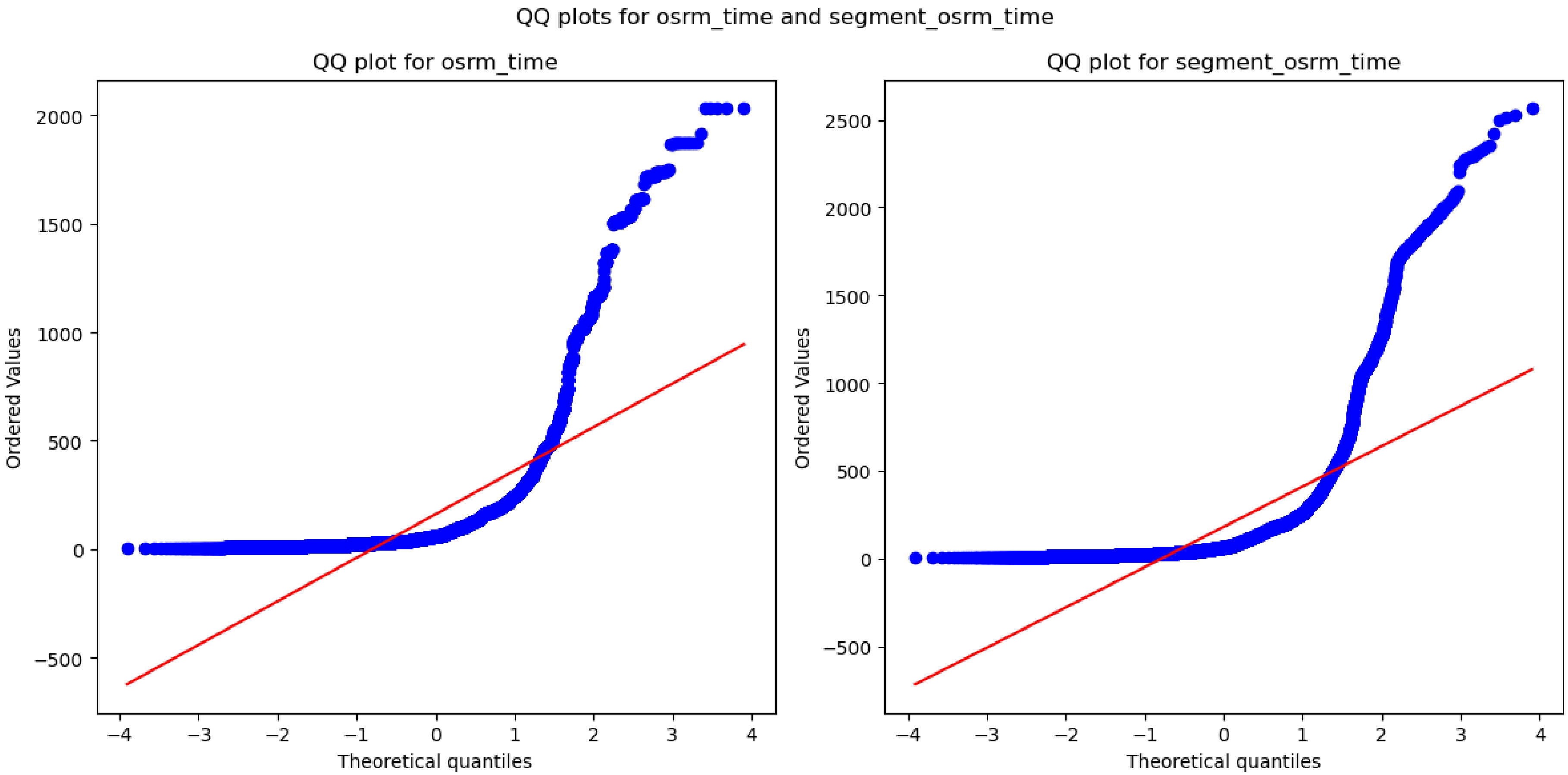
In [93]:
```
plot_dist('osrm_time', 'segment_osrm_time')
```

```
Axes(0.125,0.11;0.352273x0.77)
Axes(0.547727,0.11;0.352273x0.77)
```



In [94]:
```
qq_plot('osrm_time', 'segment_osrm_time')
```

```
((array([-3.90622638, -3.68627647, -3.56575533, ...,  3.56575533,
        3.68627647,  3.90622638]), array([   6.,    7.,    7., ..., 2031., 2032., 2032.])), (200.5670444872438, 160.
9909379860688, 0.7386864311178046))
((array([-3.90622638, -3.68627647, -3.56575533, ...,  3.56575533,
        3.68627647,  3.90622638]), array([   6.,    7.,    7., ..., 2510., 2530., 2564.])), (229.50023920260057, 18
0.51159802529244, 0.7291562091105451))
```



In [95]:
```
levene_test('osrm_time', 'segment_osrm_time')
```

```
p_value 9.250556006347759e-08
```

Out[95]:
```
'The samples do not have  Homogenous Variance'
```

In [96]:
```
shapiro_test('osrm_time', 'segment_osrm_time')
```

```
p_value 6.80854895433023e-19
p_value 2.0233150754491152e-23
```

Out[96]:
```
('The sample does not follow normal distribution',
 'The sample does not follow normal distribution')
```

In [97]:

```
boxcox_values4 = boxcox_test('osrm_time', 'segment_osrm_time')
boxcox_values4.head()
```

Out[97]:

	osrm_time_boxcox	segment_osrm_time_boxcox
0	3.520374	3.812051
1	2.774050	2.863631
2	3.716826	3.973453
3	2.052965	2.145702
4	2.980870	3.104451

In [98]:

```
# Shapiro-Wilk test for normality

def shapiro_test4(col1, col2):
    sample1 = boxcox_values4[col1].sample(200)
    sample2 = boxcox_values4[col2].sample(200)

    #testing for col1
    t_stat, p_value = st.shapiro(sample1)
    print('p_value', p_value)
    if p_value < 0.05:
        rel1 = ('The sample does not follow normal distribution')
    else:
        rel1 = ('The sample follows normal distribution')

    # tetsing for col2
    t_stat, p_value = st.shapiro(sample2)
    print('p_value', p_value)
    if p_value < 0.05:
        rel2 = ('The sample does not follow normal distribution')
    else:
        rel2 = ('The sample follows normal distribution')
    return (rel1, rel2)
```

In [99]:
```
shapiro_test4('osrm_time_boxcox','segment_osrm_time_boxcox')
```

```
p_value 0.04088500514626503
p_value 0.05447032302618027
```

Out[99]:
```
('The sample does not follow normal distribution',
 'The sample follows normal distribution')
```

In [100…
```
t_stat, p_value = st.mannwhitneyu(df_aggid['osrm_distance'], df_aggid['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 1.0001087659092072e-06
The samples are not similar
```

Since the p-value is less than the significance level (α), we reject the null hypothesis. Therefore, it can be concluded that `osrm_time` and `segment_osrm_time` are not statistically similar.

Outliers on the numerical variables

In [101…
```
num_cols = df_aggid[['start_scan_to_end_scan', 'actual_distance_to_destination',
           'actual_time', 'osrm_time', 'osrm_distance', 'segment_actual_time',
            'segment_osrm_time', 'segment_osrm_distance']]
```

In [102…
```
num_cols.describe().T
```

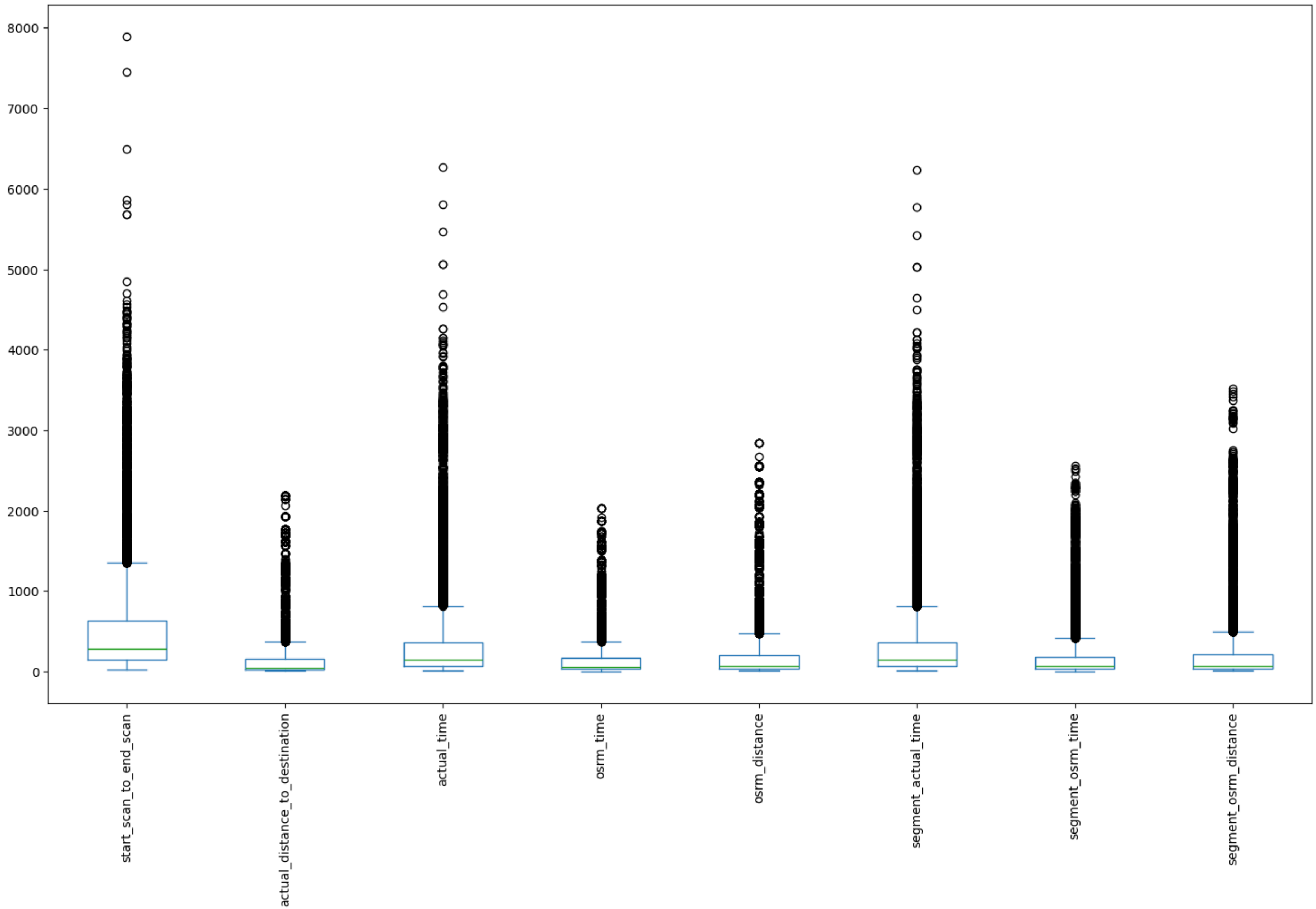
Out[102…

	count	mean	std	min	25%	50%	75%	max
start_scan_to_end_scan	14787.0	529.429025	658.254936	23.000000	149.000000	279.000000	632.000000	7898.000000
actual_distance_to_destination	14787.0	164.090196	305.502982	9.002461	22.777099	48.287894	163.591258	2186.531787

actual_time	14787.0	356.306012	561.517936	9.000000	67.000000	148.000000	367.000000	6265.000000
osrm_time	14787.0	160.990938	271.459495	6.000000	29.000000	60.000000	168.000000	2032.000000
osrm_distance	14787.0	203.887411	370.565564	9.072900	30.756900	65.302800	206.644200	2840.081000
segment_actual_time	14787.0	353.059174	556.365911	9.000000	66.000000	147.000000	364.000000	6230.000000
segment_osrm_time	14787.0	180.511598	314.679279	6.000000	30.000000	65.000000	184.000000	2564.000000
segment_osrm_distance	14787.0	222.705466	416.846279	9.072900	32.578850	69.784200	216.560600	3523.632400

In [103…

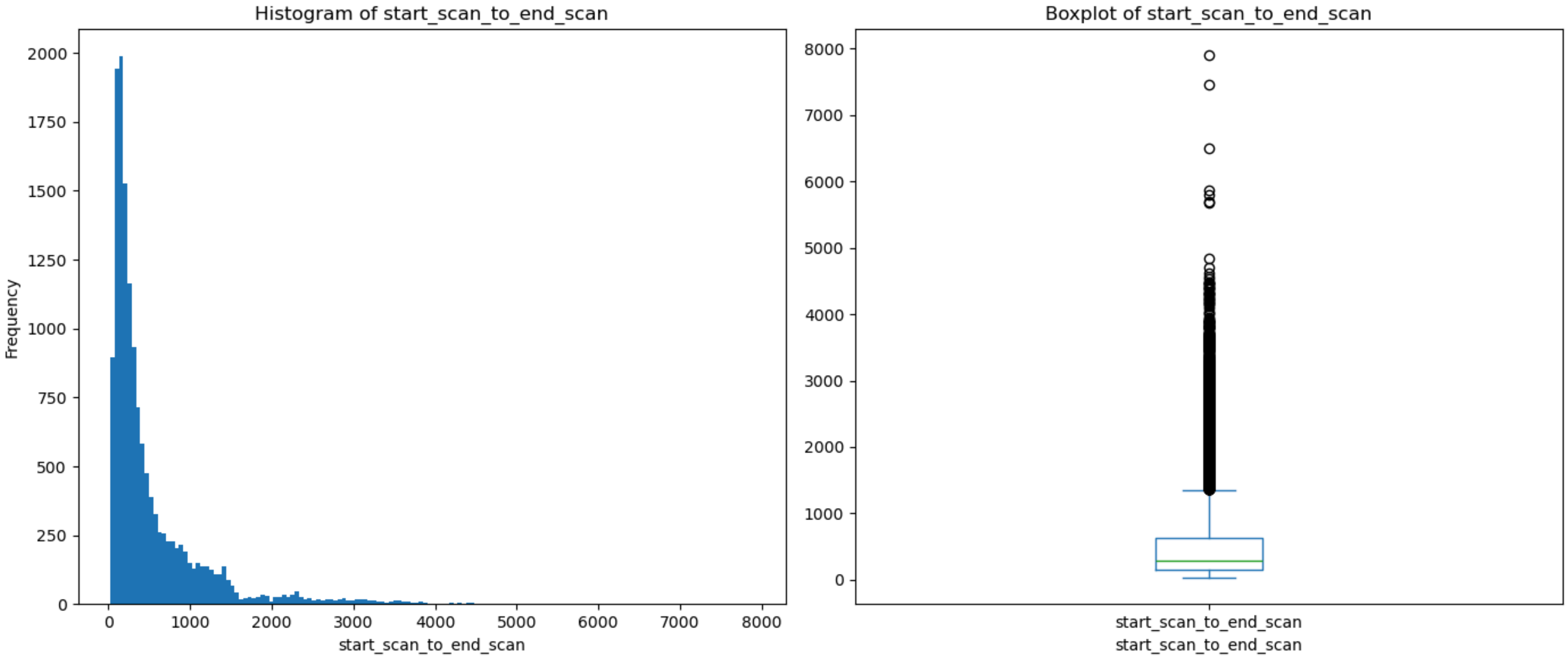
```
num_cols.plot(kind='box', figsize=(18,10))
plt.xticks(rotation=90)
plt.show()
```

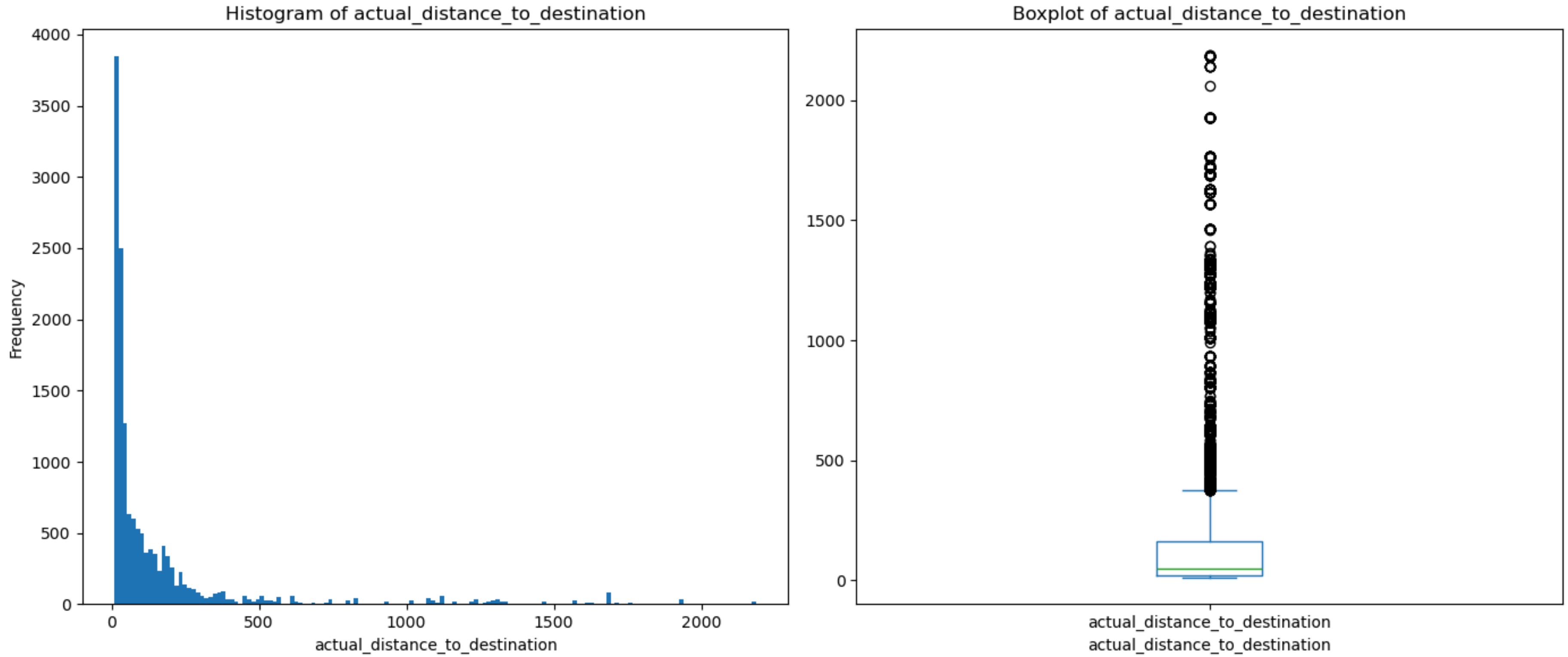


In [104…

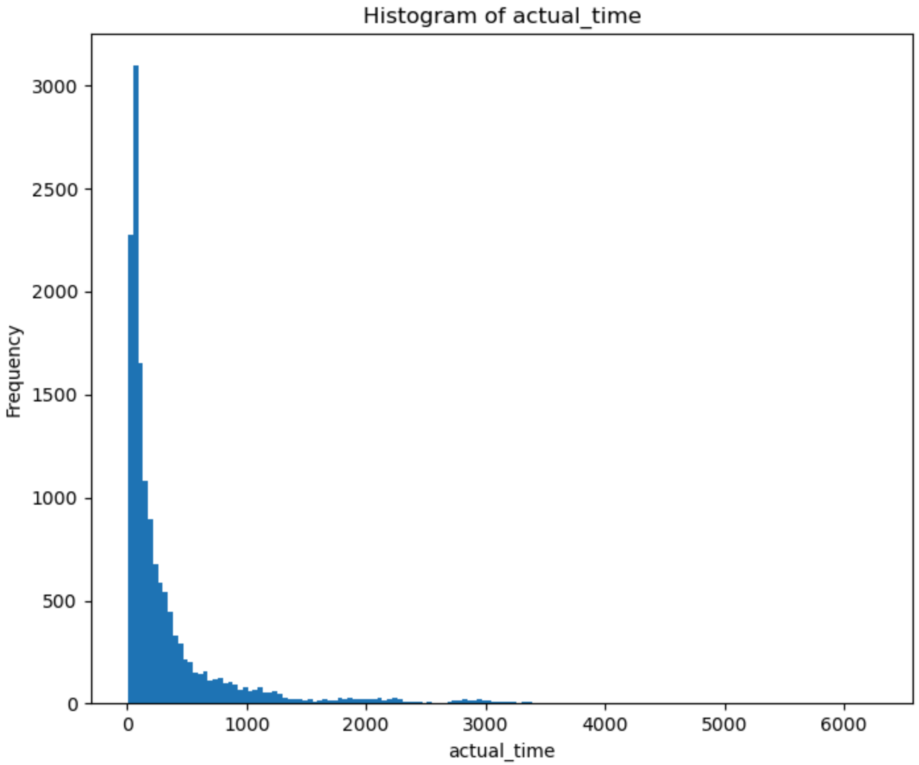
```
# IQR Method
for i, col in enumerate(num_cols):
```

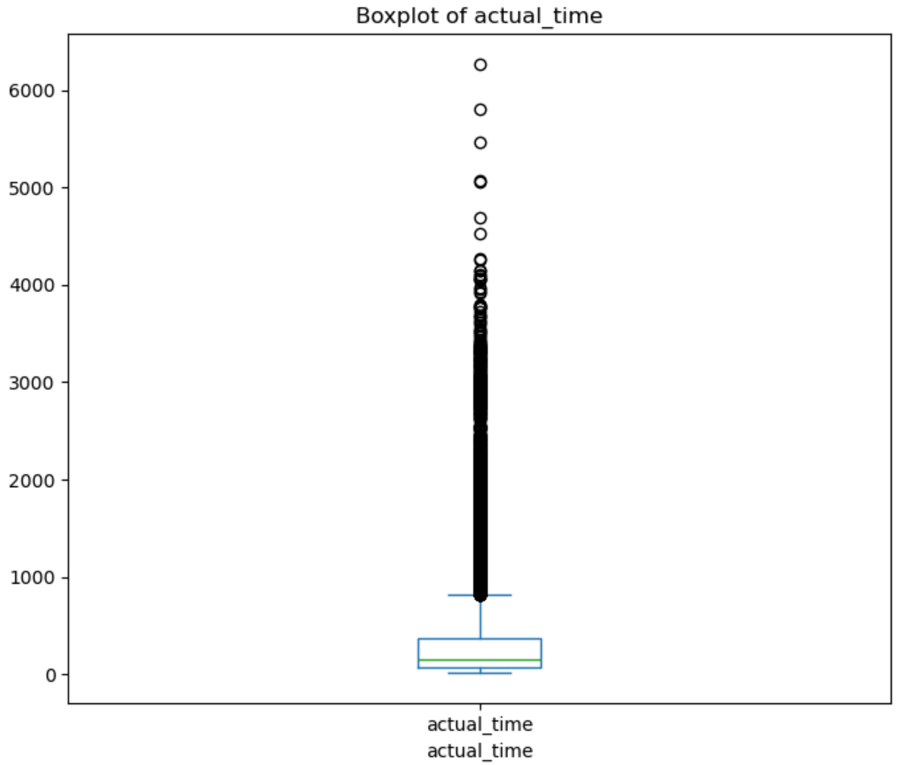
```python
plt.figure(figsize=(14, 6))   # Slightly wider for two subplots

# Plot 1: Histogram
plt.subplot(1, 2, 1)
df_aggid[col].plot(kind='hist', bins=150, title=f'Histogram of {col}')
plt.xlabel(col)
plt.ylabel('Frequency')

# Plot 2:
plt.subplot(1, 2, 2)
df_aggid[col].plot(kind='box', title=f'Boxplot of {col}')
plt.xlabel(col)

plt.tight_layout()
plt.show()
```

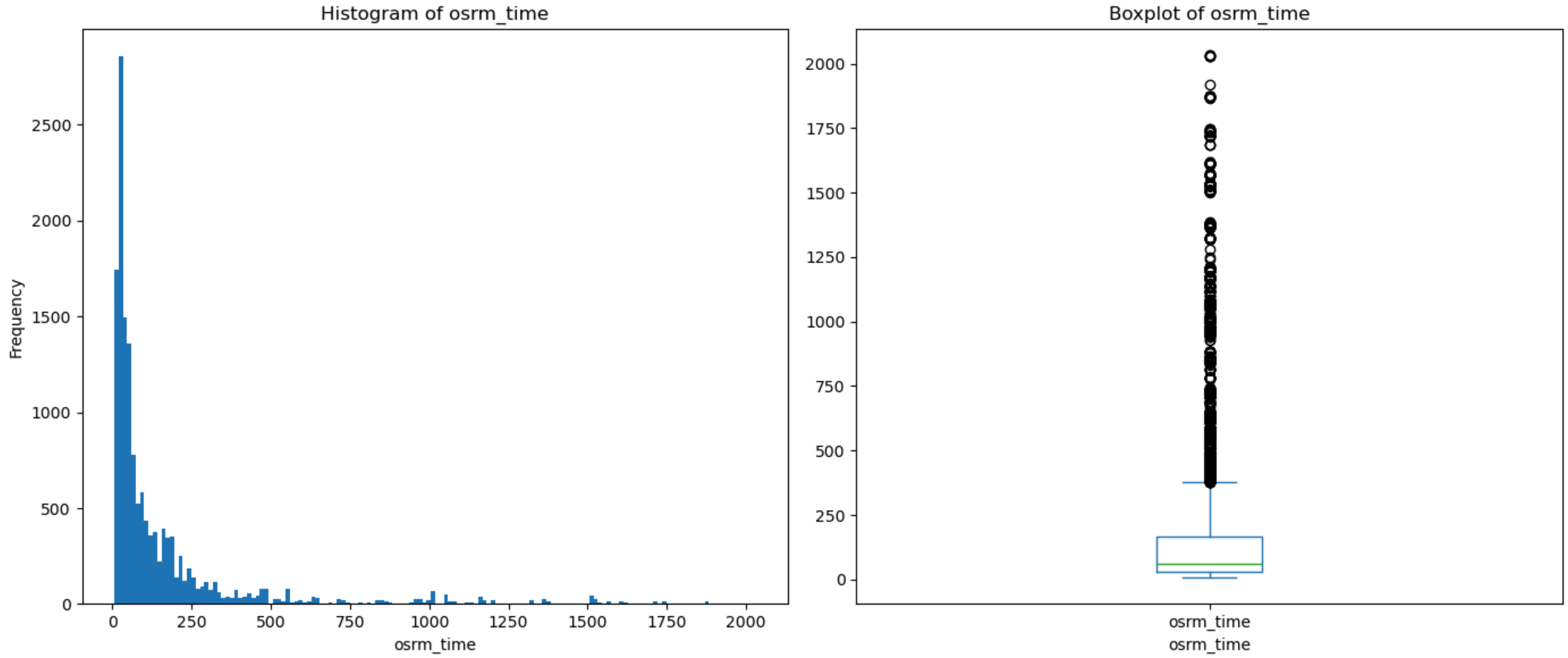




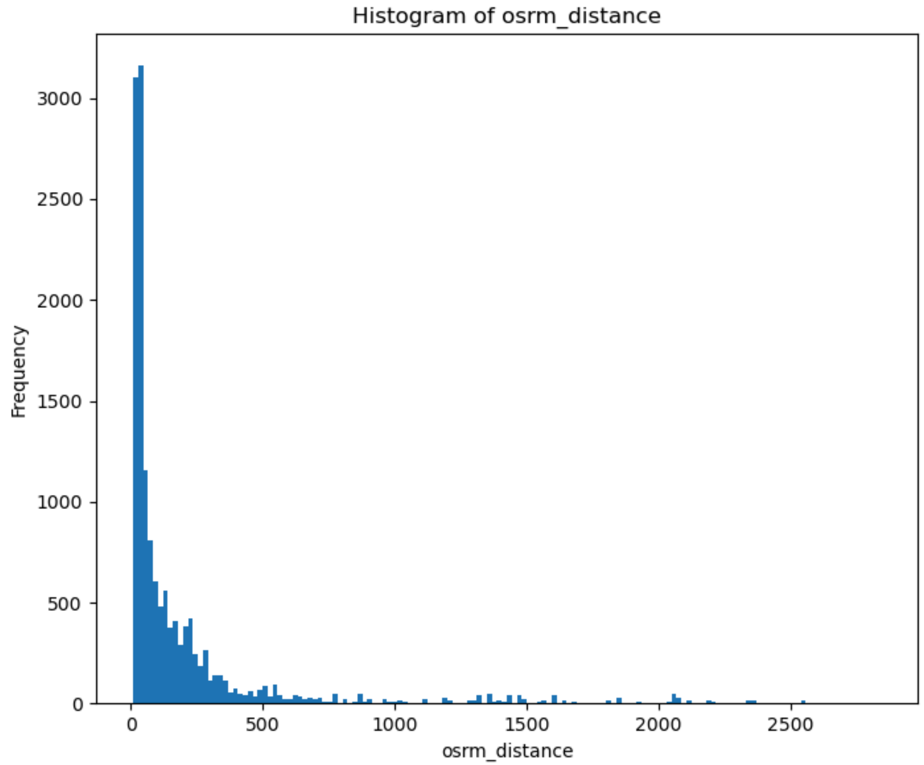
Histogram of actual_distance_to_destination
Frequency
0
500
1000
1500
2000
2500
3000
3500
4000
0
500
1000
1500
2000
actual_distance_to_destination
Boxplot of actual_distance_to_destination
0
500
1000
1500
2000
actual_distance_to_destination
actual_distance_to_destination

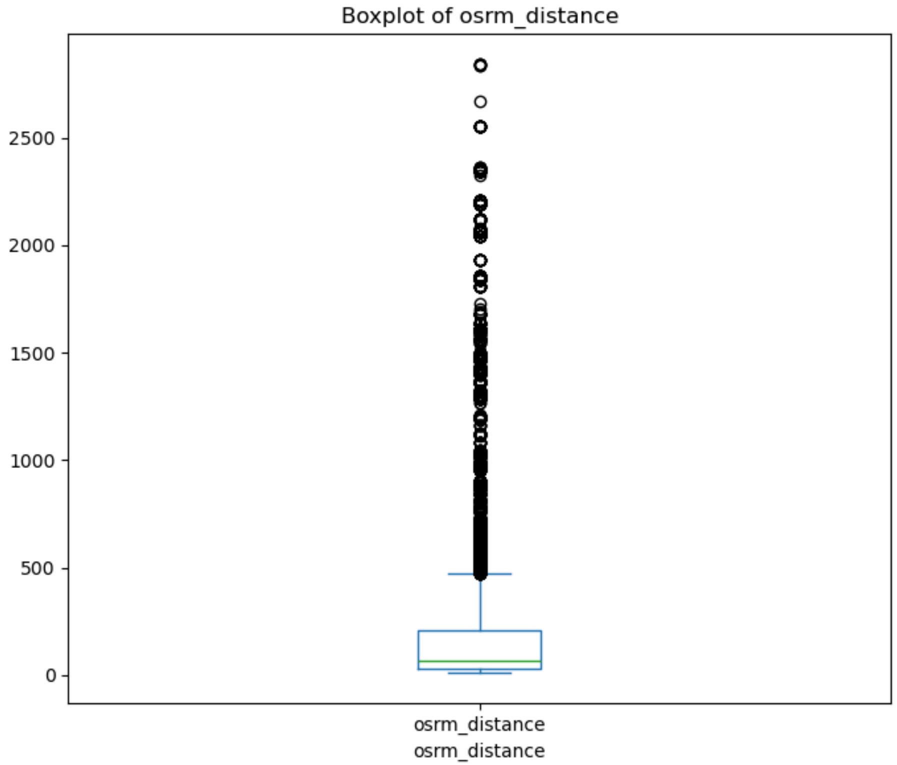

Histogram of actual_time
Frequency
actual_time
0
500
1000
1500
2000
2500
3000
0
1000
2000
3000
4000
5000
6000

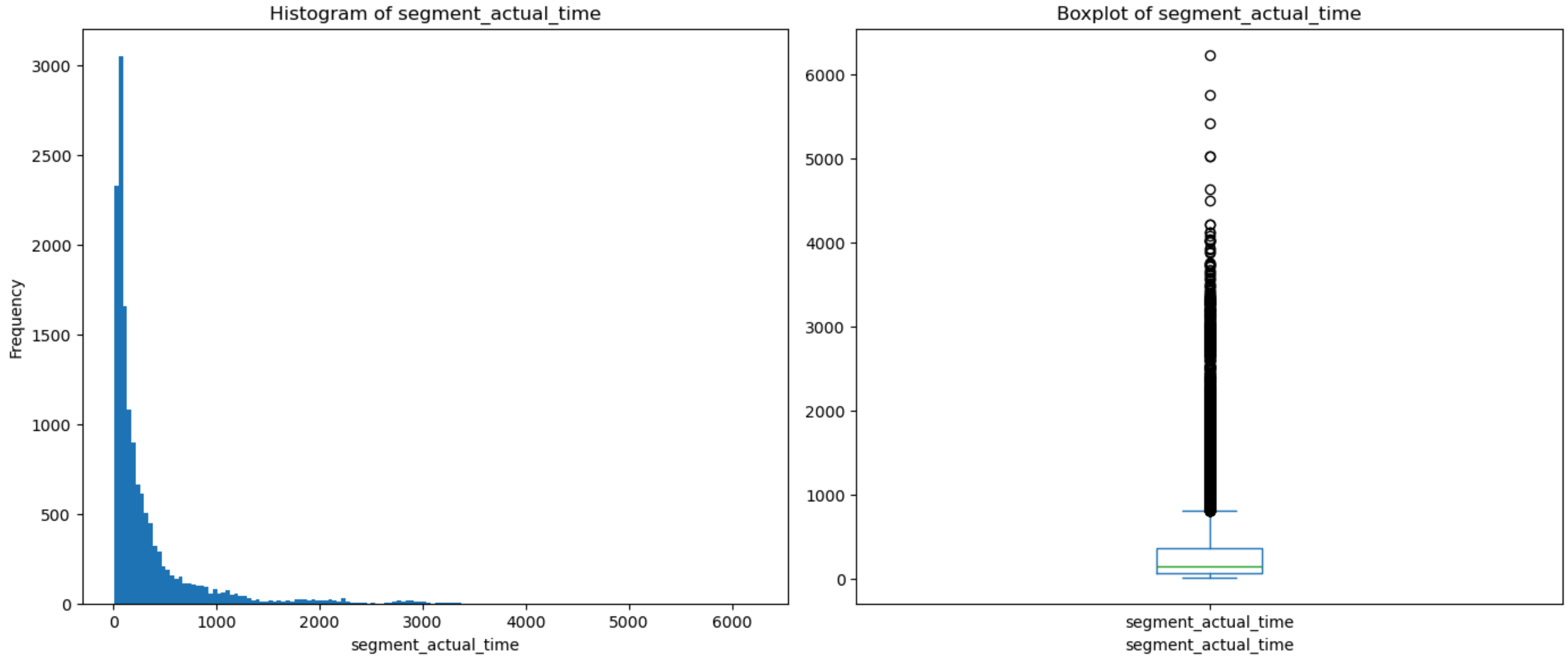

Boxplot of actual_time
0
1000
2000
3000
4000
5000
6000
actual_time
actual_time

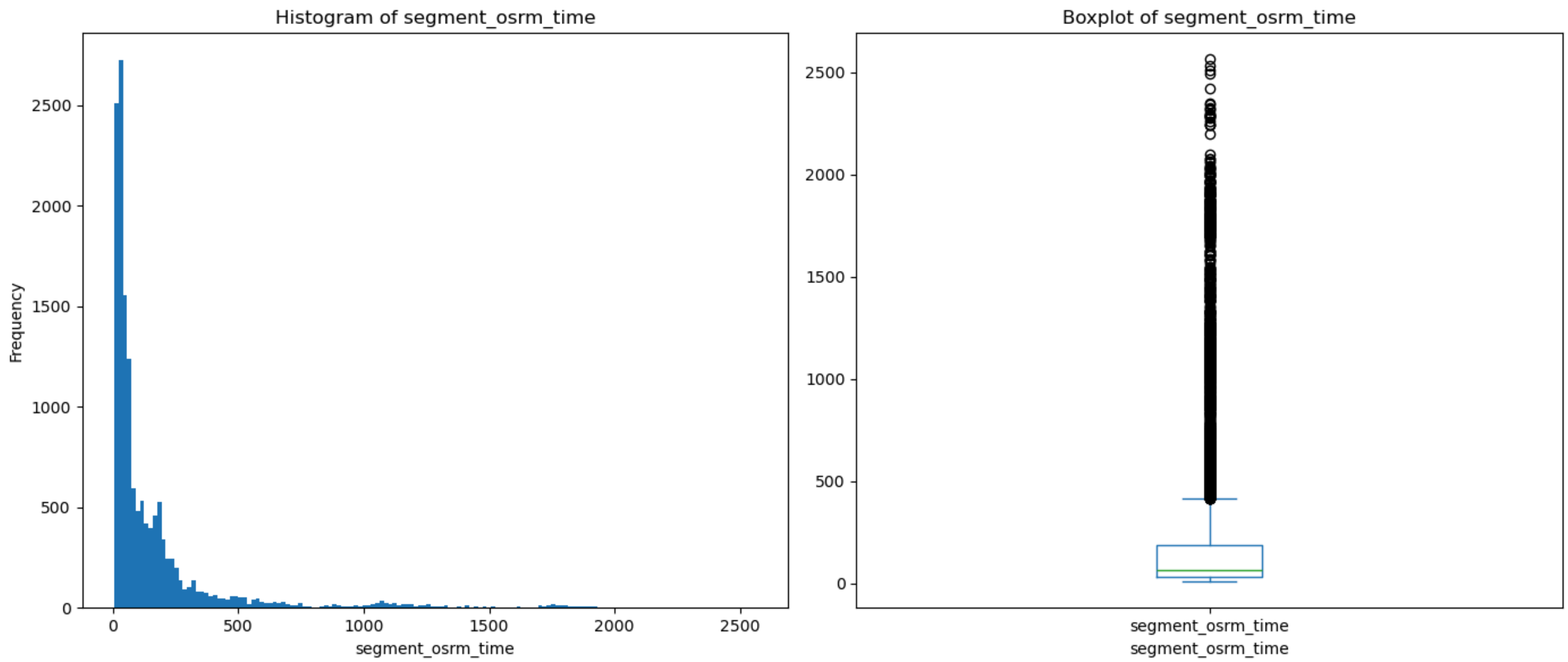


Histogram of osrm_time
Frequency
osrm_time
Boxplot of osrm_time
osrm_time
osrm_time

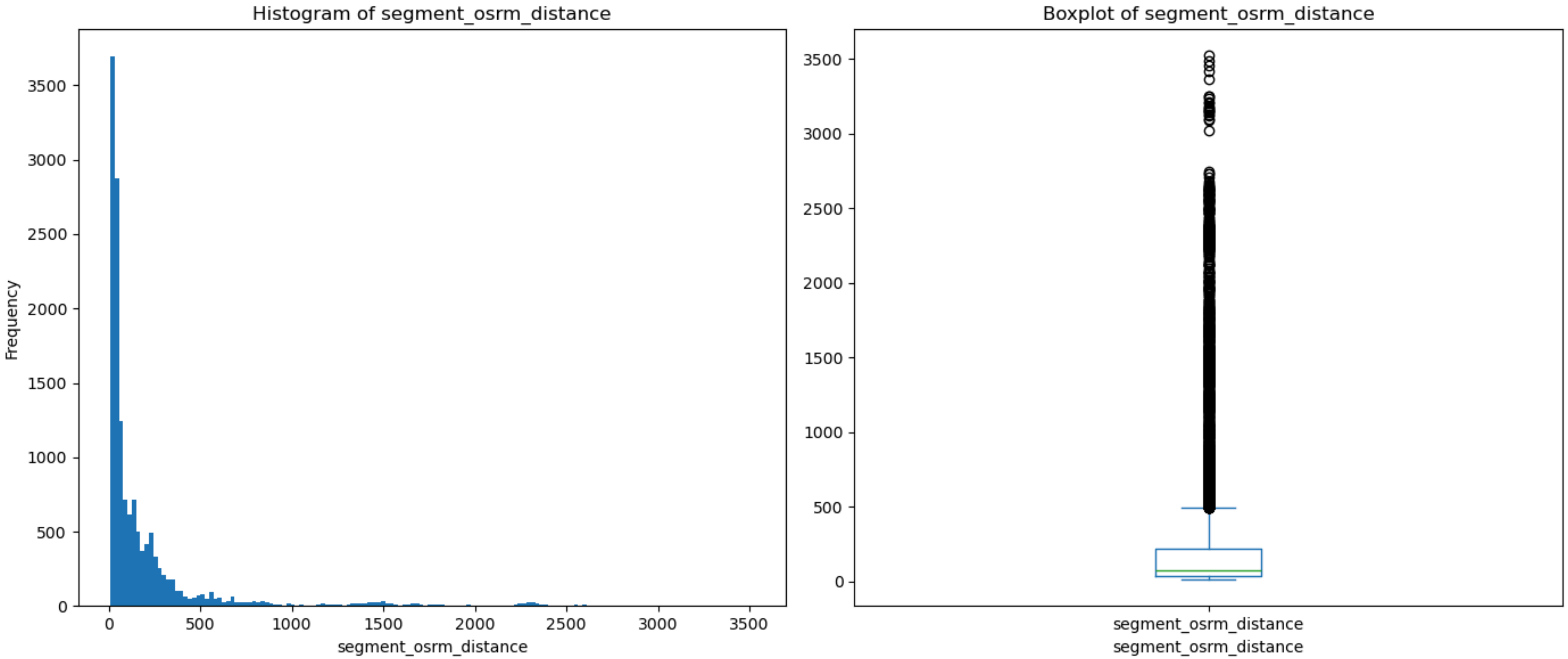

Histogram of osrm_distance
Frequency
osrm_distance
0
500
1000
1500
2000
2500
3000


Boxplot of osrm_distance
osrm_distance
osrm_distance
0
500
1000
1500
2000
2500


Histogram of segment_actual_time
Frequency
segment_actual_time
Boxplot of segment_actual_time
segment_actual_time
segment_actual_time



Histogram of segment_osrm_time
Frequency
segment_osrm_time
0
500
1000
1500
2000
2500
Boxplot of segment_osrm_time
segment_osrm_time
segment_osrm_time



In [105…

```
# start_scan_to_end_scan

for i in num_cols:
    print(f'Outliers of {i}:')
    # print()
    percentile25 = np.quantile(df_aggid[i], 0.25)
    percentile75 = np.quantile(df_aggid[i], 0.75)
    iqr = percentile75 - percentile25
    upper_bond = percentile75 + iqr*1.5
    lower_bond = percentile25 - iqr*1.5
    outliers = df_aggid.loc[(df_aggid[i] > upper_bond) | (df_aggid[i] < lower_bond)]
    print(f'Number of outliers : {outliers.shape[0]}')
    print('percentile 25 is: ', percentile25,'\nPercentile 75 is: ', percentile75,
          '\nIQR is: ', iqr, '\nUpper bond is: ', upper_bond, '\nLower Bond is: ', lower_bond)
    print('_ _'*30)
```

```
Outliers of start_scan_to_end_scan:
Number of outliers : 1282
percentile 25 is:  149.0
Percentile 75 is:  632.0
IQR is:  483.0
Upper bond is:  1356.5
Lower Bond is:  -575.5
_ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ _
Outliers of actual_distance_to_destination:
Number of outliers : 1452
percentile 25 is:  22.777098943155323
Percentile 75 is:  163.5912581579725
IQR is:  140.81415921481718
Upper bond is:  374.81249698019826
Lower Bond is:  -188.44413987907043
_ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ _
Outliers of actual_time:
Number of outliers : 1646
percentile 25 is:  67.0
Percentile 75 is:  367.0
IQR is:  300.0
Upper bond is:  817.0
Lower Bond is:  -383.0
_ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ _
Outliers of osrm_time:
Number of outliers : 1506
percentile 25 is:  29.0
Percentile 75 is:  168.0
IQR is:  139.0
Upper bond is:  376.5
Lower Bond is:  -179.5
_ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ _
Outliers of osrm_distance:
Number of outliers : 1522
percentile 25 is:  30.7569
Percentile 75 is:  206.6442
IQR is:  175.8873
Upper bond is:  470.47515000000004
Lower Bond is:  -233.07405000000003
_ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ _
Outliers of segment_actual_time:
```

```
Number of outliers : 1644
percentile 25 is:  66.0
Percentile 75 is:  364.0
IQR is:  298.0
Upper bond is:  811.0
Lower Bond is:  -381.0
_ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ _
Outliers of segment_osrm_time:
Number of outliers : 1485
percentile 25 is:  30.0
Percentile 75 is:  184.0
IQR is:  154.0
Upper bond is:  415.0
Lower Bond is:  -201.0
_ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ _
Outliers of segment_osrm_distance:
Number of outliers : 1550
percentile 25 is:  32.57885
Percentile 75 is:  216.5606
IQR is:  183.98174999999998
Upper bond is:  492.533225
Lower Bond is:  -243.393775
_ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ __ _
```

Exploratory Outliers Analysis Summary

- **Outliers** are present in **all columns** of the dataset.
- The **highest concentration of outliers** is observed in the `actual_time` and `segment_actual_time` columns.
- The **least number of outliers** are found in the `start_scan_to_end_scan` column.
- Based on visualizations (e.g., histograms and boxplots), **all columns exhibit right-skewed distributions**.
- Given the skewness and the presence of extreme values, applying the **IQR (Interquartile Range) method** is an appropriate approach for handling outliers.

One-hot encoding of categorical variables

In [106…
```
df_aggid['route_type'].value_counts()
```

Out[106…
```
route_type
Carting     8906
FTL         5881
Name: count, dtype: int64
```

In [107…
```
df_aggid[['Carting_encoded', 'FTL_encoded']] = pd.get_dummies(df_aggid['route_type']).astype(int)
df_aggid[['Carting_encoded', 'FTL_encoded']].head()
```

Out[107…

	Carting_encoded	FTL_encoded
0	0	1
1	1	0
2	0	1
3	1	0
4	0	1

Normalize/ Standardize the numerical features using MinMaxScaler or StandardScaler

In [108…
```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
```

In [109…
```
std_cols = df_aggid[['start_scan_to_end_scan', 'actual_distance_to_destination',
                     'actual_time', 'osrm_time', 'osrm_distance', 'segment_actual_time', 'segment_osrm_time', 'segme
std_cols = std_cols.columns.tolist()
std_cols
```

Out[109…
```
['start_scan_to_end_scan',
 'actual_distance_to_destination',
```

```
 'actual_time',
 'osrm_time',
 'osrm_distance',
 'segment_actual_time',
 'segment_osrm_time',
 'segment_osrm_distance']
```

In [110…
```
# Checking for the null valus in the numerical Columns
# This throw error is the selected columns have Null values
df_aggid[std_cols].isnull().sum()
```

Out[110…
```
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
```

In [111…
```
# Initializing the MinMaxScaler
scaler = MinMaxScaler()
```

In [112…
```
# Applying on the numerical columns
df_aggid[std_cols] = scaler.fit_transform(df_aggid[std_cols])
```

In [113…
```
# After MinmaxSecaler Applying
df_aggid[std_cols].min()
```

Out[113…
```
start_scan_to_end_scan            0.0
actual_distance_to_destination    0.0
actual_time                       0.0
osrm_time                         0.0
osrm_distance                     0.0
segment_actual_time               0.0
segment_osrm_time                 0.0
segment_osrm_distance             0.0
dtype: float64
```

In [114…

```python
# After MinmaxSecaler Applying
df_aggid[std_cols].max()
```

Out[114…

```
start_scan_to_end_scan            1.0
actual_distance_to_destination    1.0
actual_time                       1.0
osrm_time                         1.0
osrm_distance                     1.0
segment_actual_time               1.0
segment_osrm_time                 1.0
segment_osrm_distance             1.0
dtype: float64
```

In [115…

```python
df_aggid[std_cols].head()
```

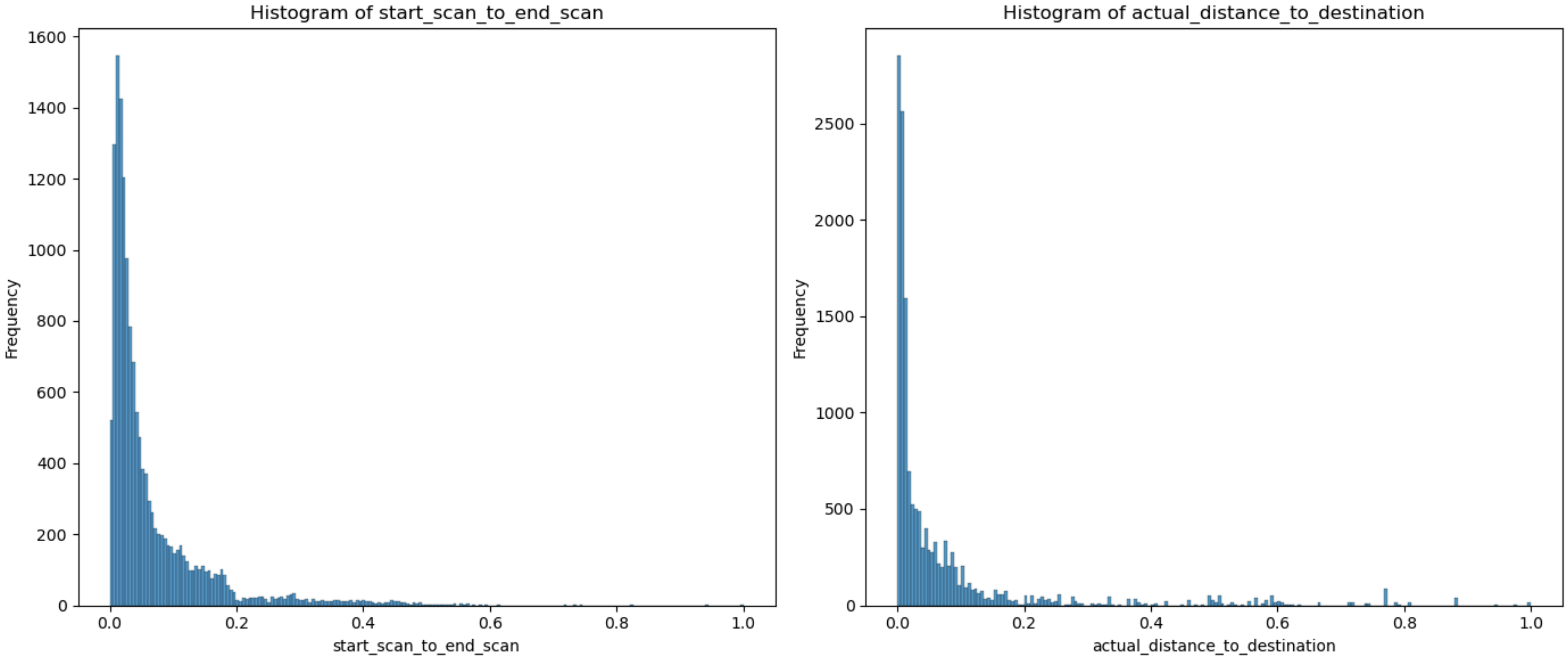
Out[115…

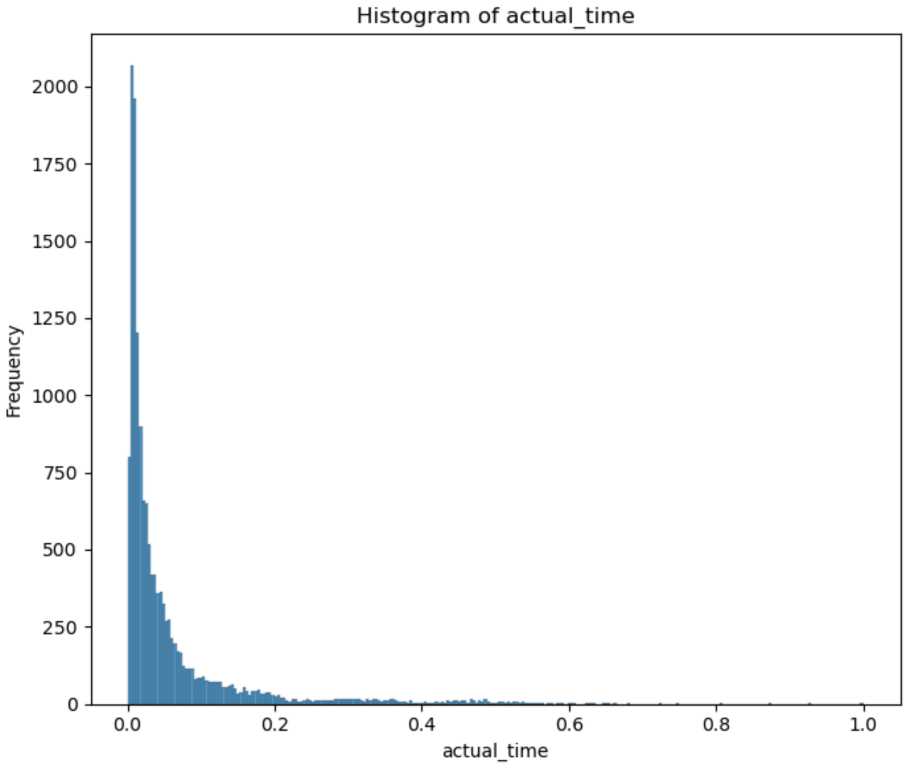
	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_time	segment_osrm_time	se
0	0.283937	0.374613	0.248242	0.350938	0.346972	0.247388	0.391712	
1	0.019937	0.029476	0.021419	0.030602	0.026859	0.021218	0.023065	
2	0.496508	0.880999	0.533568	0.855874	0.828325	0.530301	0.756450	
3	0.009778	0.003753	0.007992	0.004442	0.003747	0.008037	0.003909	
4	0.088127	0.054395	0.053069	0.054788	0.048647	0.053207	0.042611	

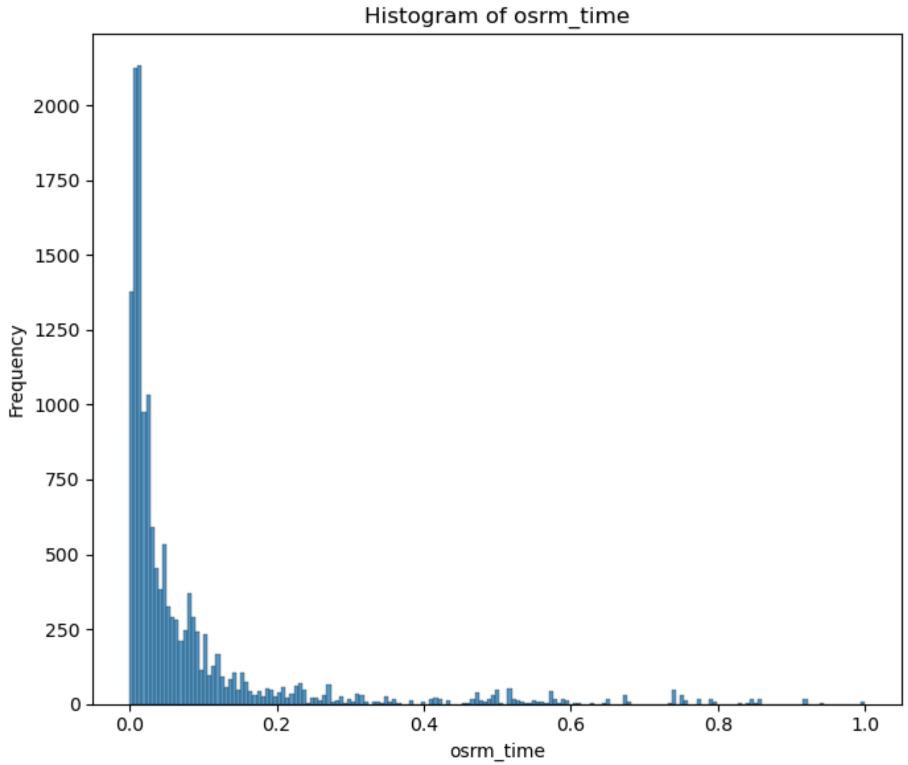
In [116…

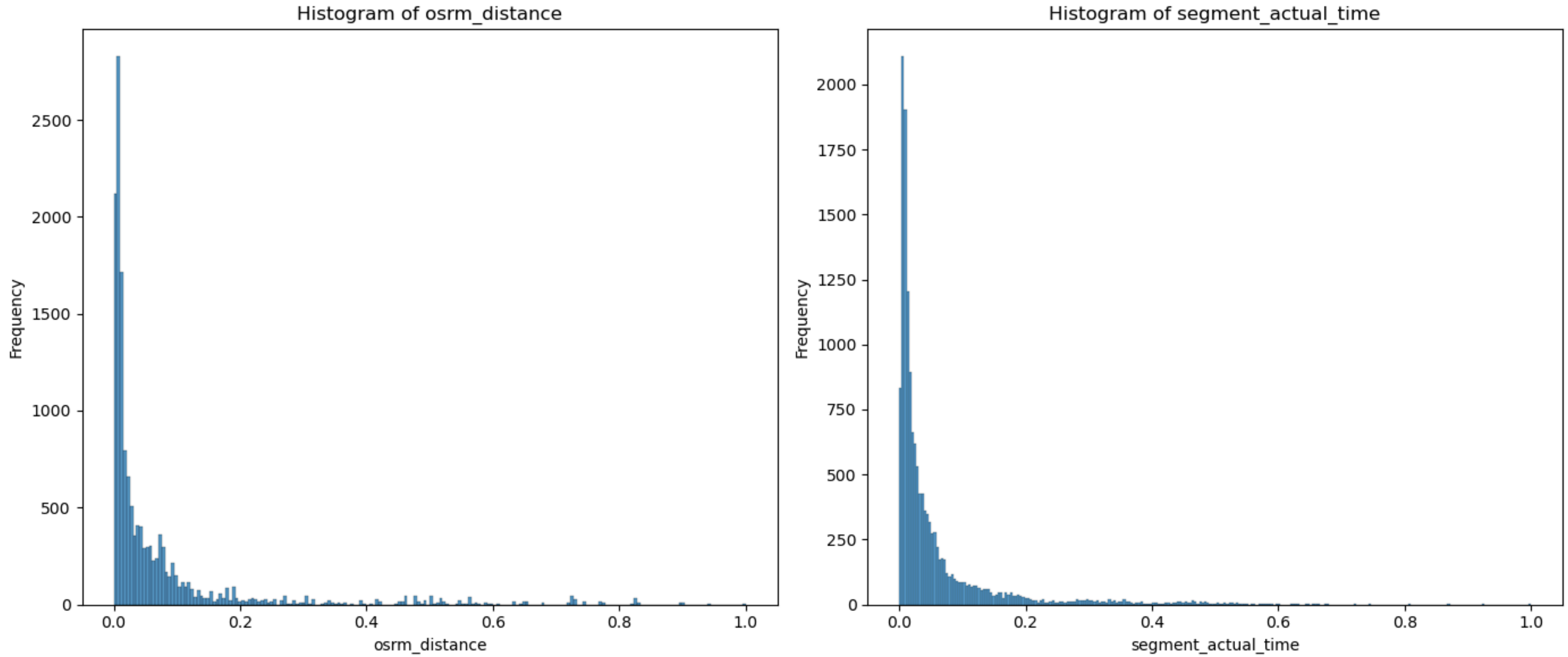
```python
for i in range(0, len(std_cols), 2):
    plt.figure(figsize=(14, 6))

    for j in range(2):
        if i + j < len(std_cols):
            plt.subplot(1, 2, j+1)
            col = std_cols[i + j]
            sns.histplot(df_aggid[col])
            plt.title(f'Histogram of {col}')
            plt.xlabel(col)
            plt.ylabel('Frequency')
```

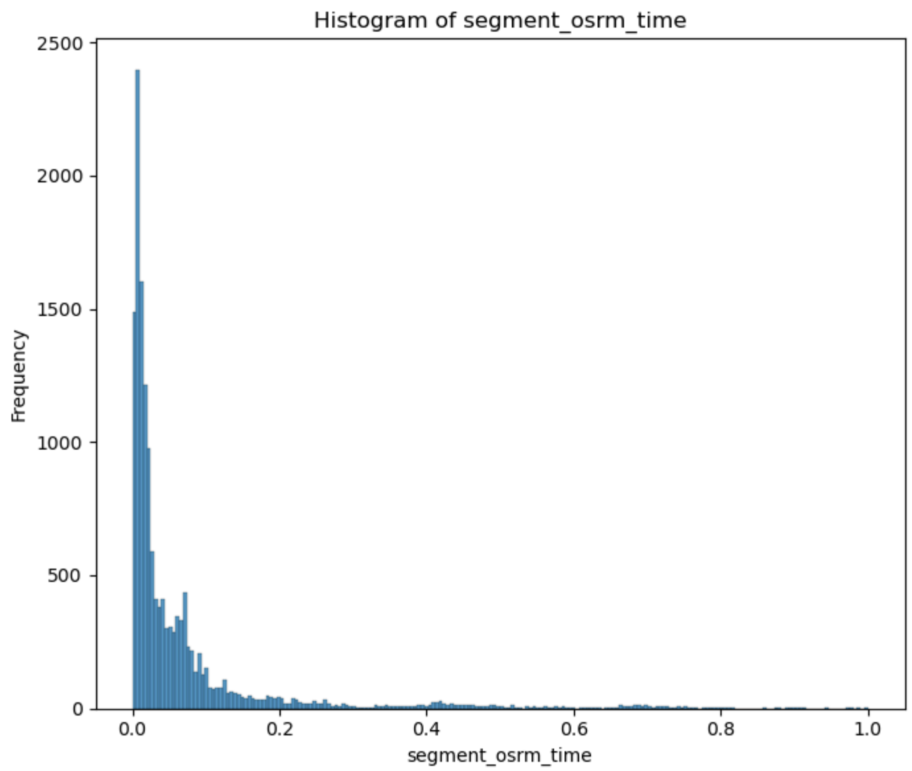
```
plt.tight_layout()
plt.show()
```

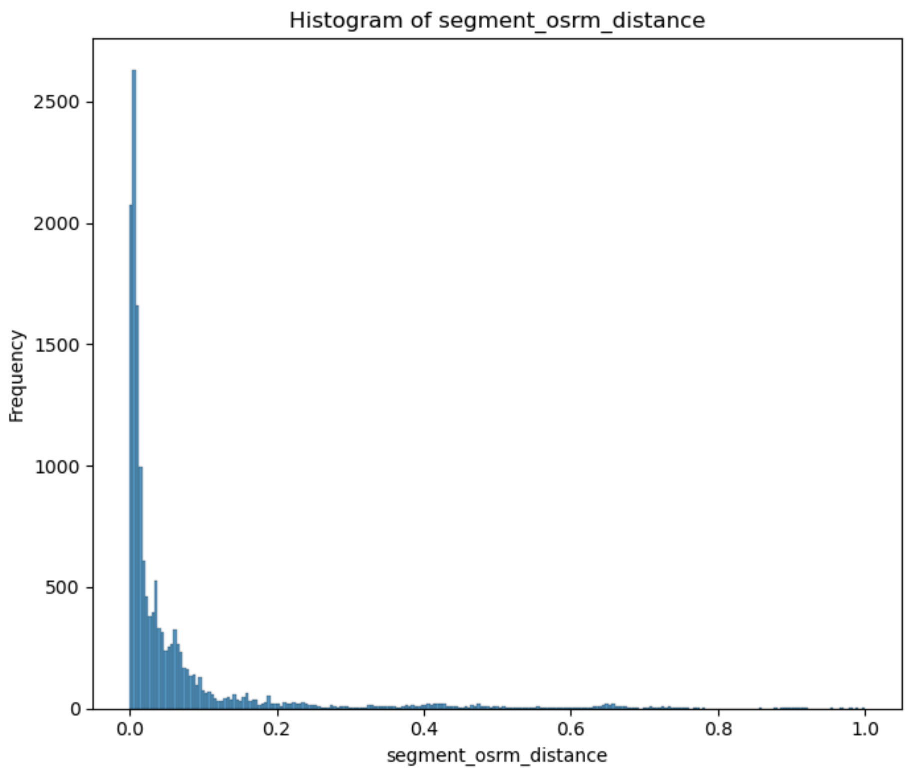



Histogram of actual_time
Frequency
actual_time
0
250
500
750
1000
1250
1500
1750
2000
0.0
0.2
0.4
0.6
0.8
1.0


Histogram of osrm_time
Frequency
osrm_time
0
250
500
750
1000
1250
1500
1750
2000
0.0
0.2
0.4
0.6
0.8
1.0


Histogram of osrm_distance
Frequency
osrm_distance
0
500
1000
1500
2000
2500
0.0
0.2
0.4
0.6
0.8
1.0
Histogram of segment_actual_time
Frequency
segment_actual_time
0
250
500
750
1000
1250
1500
1750
2000
0.0
0.2
0.4
0.6
0.8
1.0





Visualization

In [117…

```
df_aggid.columns
```

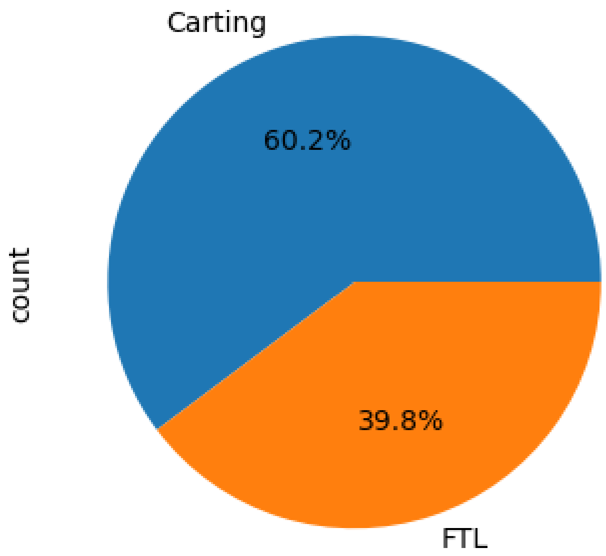
Out[117…

```
Index(['trip_uuid', 'source_center', 'destination_center', 'data',
       'route_type', 'trip_creation_time', 'source_name', 'destination_name',
       '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', 'source_state', 'source_city', 'source_place',
       'source_code', 'destination_state', 'destination_city',
       'destination_place', 'destination_code', 'year', 'month', 'week', 'day',
       'created_hour', 'time_range', 'Carting_encoded', 'FTL_encoded'],
      dtype='object')
```

In [118…

```
# cat_types = df_aggid.select_dtypes(include='int32')
df_aggid['route_type'].value_counts().plot(kind='pie',autopct='%1.1f%%', figsize=(6,4))
```

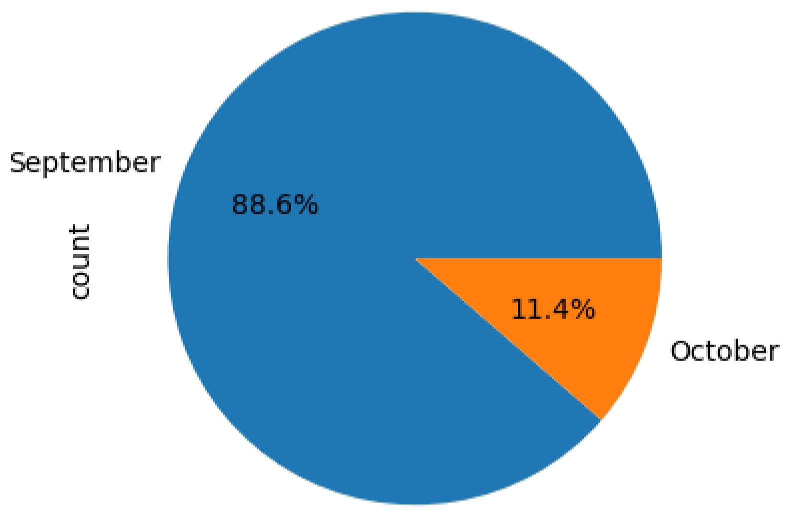
Out[118… <Axes: ylabel='count'>



In [119…

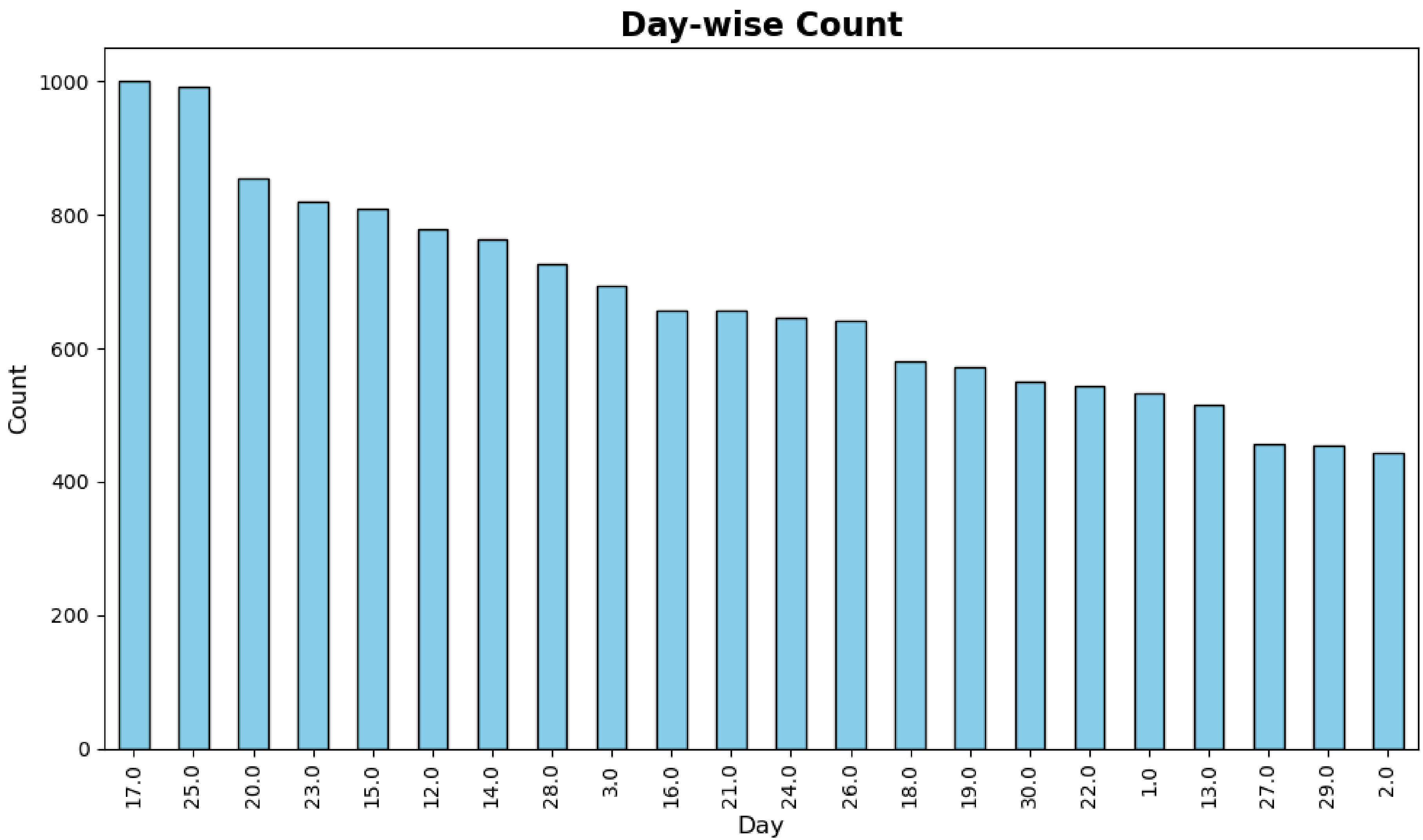
```
df_aggid['month'].value_counts().plot(kind='pie', autopct= '%1.1f%%', figsize=(6,4))
```

Out[119… <Axes: ylabel='count'>



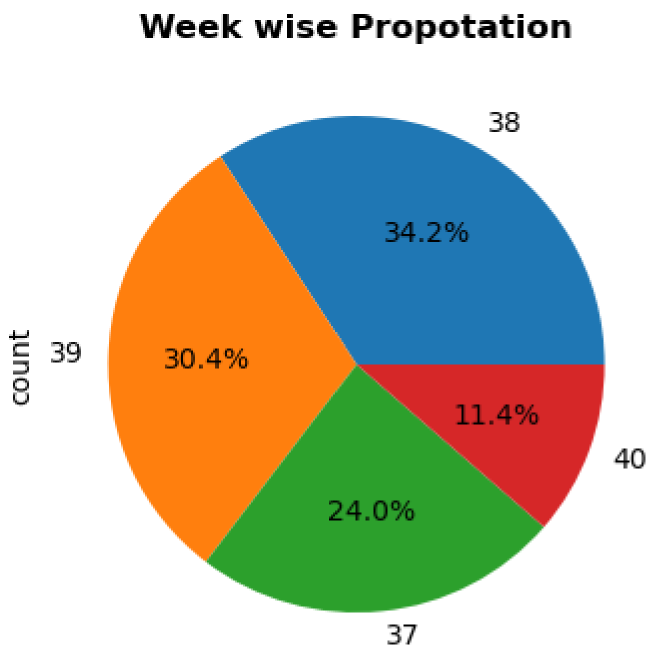
In [120…

```
df_day = df_aggid['day'].value_counts()

plt.figure(figsize=(10, 6))
df_day.plot(kind='bar', color='skyblue', edgecolor='black')

# Add labels and title
plt.title("Day-wise Count", fontsize=16, weight='bold')
plt.xlabel("Day", fontsize=12)
plt.ylabel("Count", fontsize=12)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)

plt.tight_layout()
plt.show()
```



In [121…

```
plt.title('Week wise Propotation', weight='bold')
df_aggid['week'].value_counts().plot(kind='pie', figsize=(4,6), autopct ='%1.1f%%')
plt.show()
```



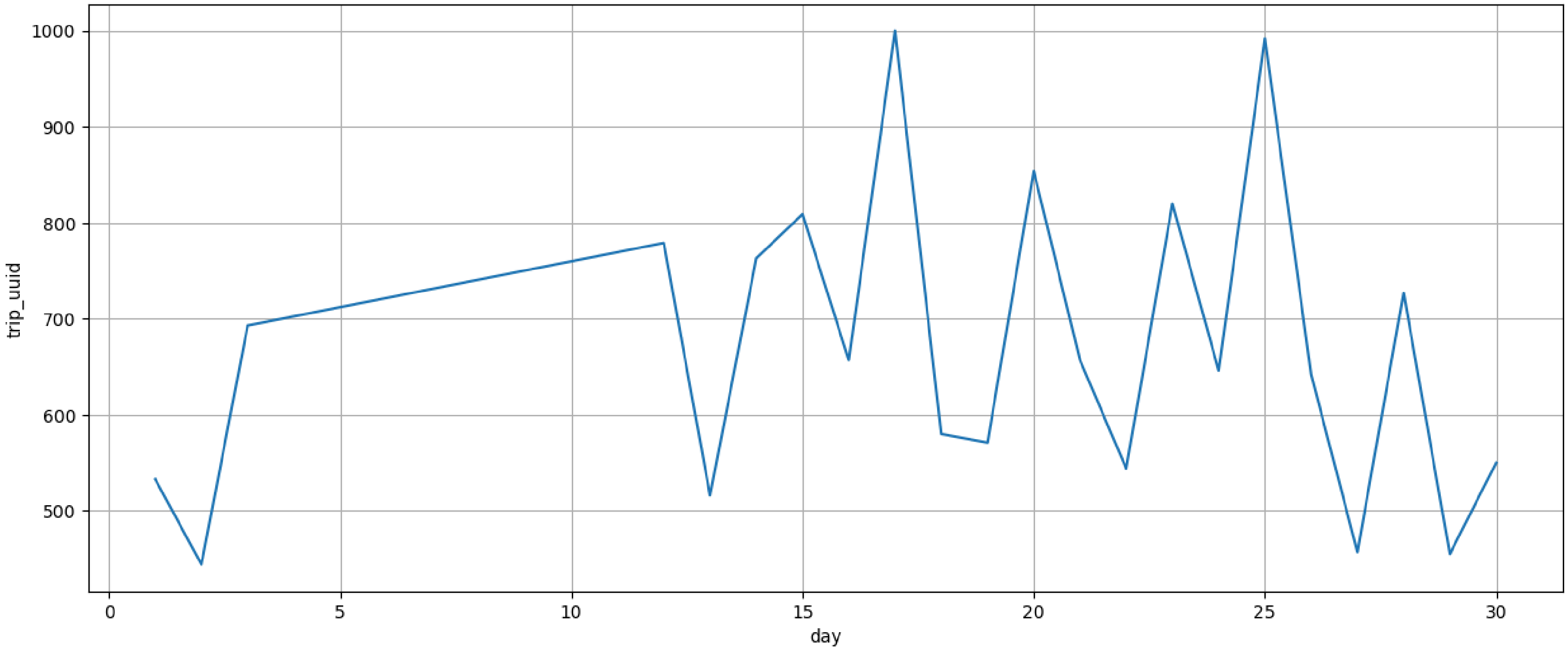
In [122…
```
day_df = df_aggid.groupby('day')['trip_uuid'].count().to_frame().reset_index()
day_df.head()
```

Out[122…

	day	trip_uuid
0	1.0	533
1	2.0	444
2	3.0	693
3	12.0	779
4	13.0	516

In [123…
```
plt.figure(figsize = (15, 6))
sns.lineplot(data=day_df,
```

```
             x=day_df['day'],
             y=day_df['trip_uuid'],
            markers = '0')
# plt.xticks(range(1, 32))
plt.grid('both')
plt.show()
```



In [124…

```
week_df = df_aggid.groupby('week')['trip_uuid'].count().reset_index()
week_df.head()
```

Out[124…

	week	trip_uuid
0	37	3524
1	38	5026

2	39	4469
3	40	1670

In [125…

```
# plt.figure(figsize = (15, 6))
# sns.lineplot(data=week_df,
#              x=week_df['week'],
#              y=week_df['trip_uuid'],
#             markers = '0')
# plt.grid('both')
# plt.plot()
```

In [126…

```
df_source_state = df_aggid.groupby('source_state')['trip_uuid'].count().sort_values(ascending=False).to_frame().rese
df_source_state['Cummulative_sum']= df_source_state['trip_uuid'].cumsum()
df_source_state['Percentage']= np.round(df_source_state['trip_uuid']/ (df_source_state['trip_uuid'].sum())*100,2)
df_source_state
```

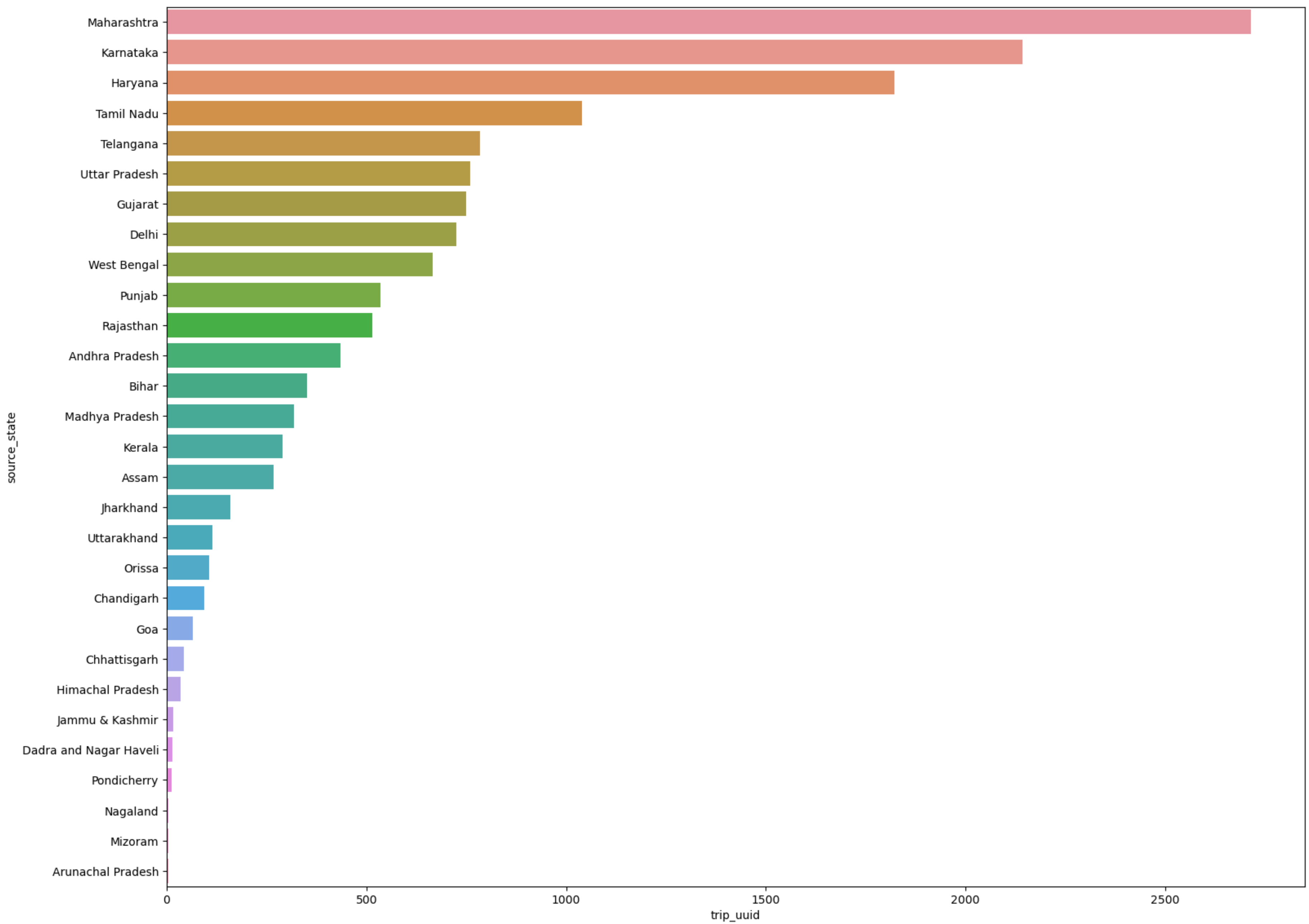
Out[126…

	source_state	trip_uuid	Cummulative_sum	Percentage
0	Maharashtra	2714	2714	18.35
1	Karnataka	2143	4857	14.49
2	Haryana	1823	6680	12.33
3	Tamil Nadu	1039	7719	7.03
4	Telangana	784	8503	5.30
5	Uttar Pradesh	760	9263	5.14
6	Gujarat	750	10013	5.07
7	Delhi	725	10738	4.90
8	West Bengal	665	11403	4.50
9	Punjab	536	11939	3.62

10	Rajasthan	514	12453	3.48
11	Andhra Pradesh	435	12888	2.94
12	Bihar	351	13239	2.37
13	Madhya Pradesh	318	13557	2.15
14	Kerala	289	13846	1.95
15	Assam	268	14114	1.81
16	Jharkhand	160	14274	1.08
17	Uttarakhand	114	14388	0.77
18	Orissa	107	14495	0.72
19	Chandigarh	93	14588	0.63
20	Goa	65	14653	0.44
21	Chhattisgarh	43	14696	0.29
22	Himachal Pradesh	34	14730	0.23
23	Jammu & Kashmir	17	14747	0.11
24	Dadra and Nagar Haveli	15	14762	0.10
25	Pondicherry	12	14774	0.08
26	Nagaland	5	14779	0.03
27	Mizoram	4	14783	0.03
28	Arunachal Pradesh	4	14787	0.03

In [127…

```
plt.figure(figsize=(18,14))
sns.barplot(data =df_source_state,
            y= df_source_state['source_state'],
            x= df_source_state['trip_uuid'])
plt.show()
```


Maharashtra
Karnataka
Haryana
Tamil Nadu
Telangana
Uttar Pradesh
Gujarat
Delhi
West Bengal
Punjab
Rajasthan
Andhra Pradesh
Bihar
Madhya Pradesh
Kerala
Assam
Jharkhand
Uttarakhand
Orissa
Chandigarh
Goa
Chhattisgarh
Himachal Pradesh
Jammu & Kashmir
Dadra and Nagar Haveli
Pondicherry
Nagaland
Mizoram
Arunachal Pradesh
source_state
0
500
1000
1500
2000
2500
trip_uuid

In [128…

```
df_source_city = df_aggid.groupby('source_city')['trip_uuid'].count().sort_values(ascending=False).to_frame().reset_
df_source_city['Cummulative_sum']= df_source_city['trip_uuid'].cumsum()
df_source_city['Percentage']= np.round(df_source_city['trip_uuid']/ (df_source_city['trip_uuid'].sum())*100,2)
df_source_city = df_source_city[:30]
df_source_city
```

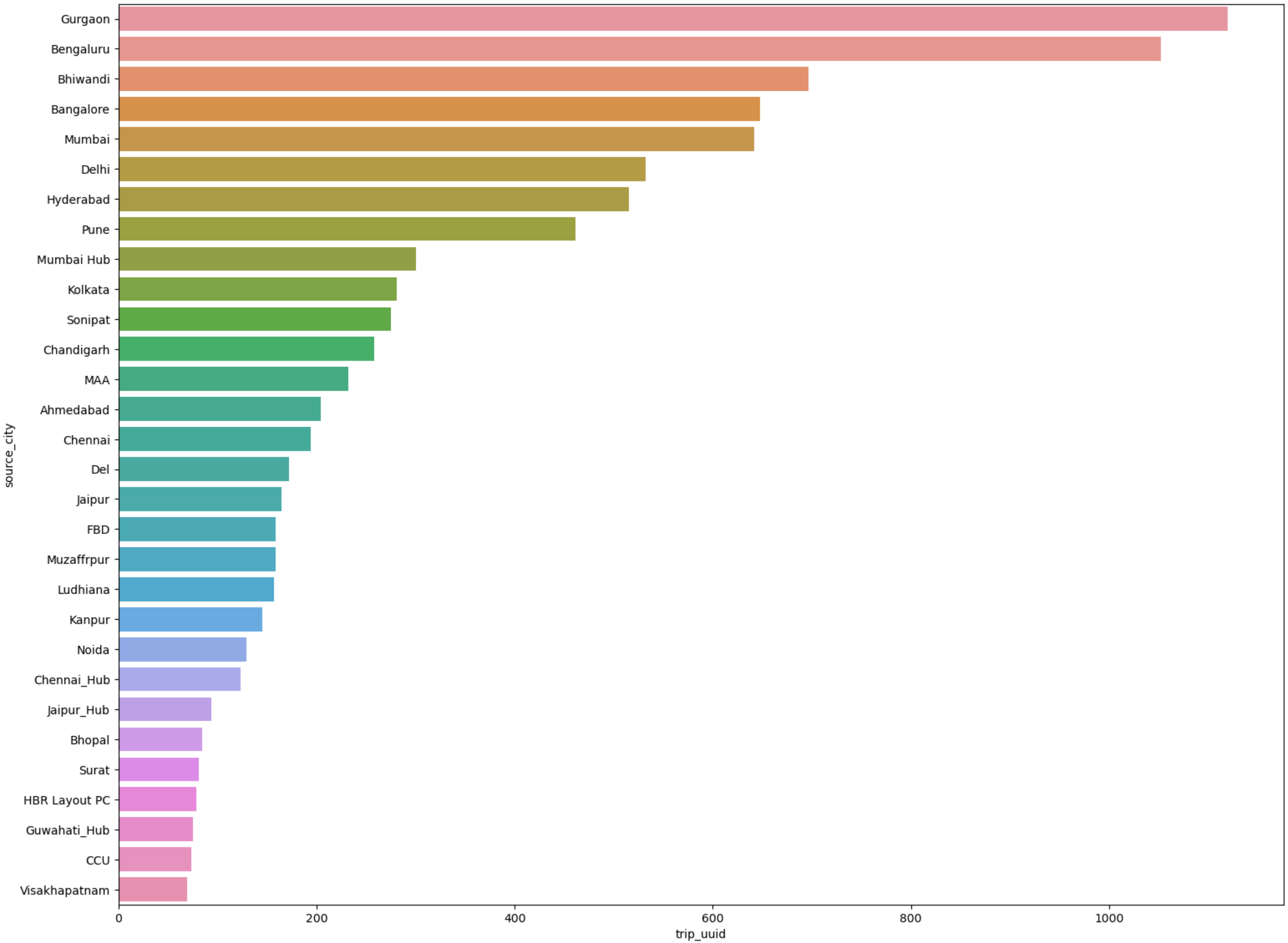
Out[128…

	source_city	trip_uuid	Cummulative_sum	Percentage
0	Gurgaon	1120	1120	7.57
1	Bengaluru	1052	2172	7.11
2	Bhiwandi	697	2869	4.71
3	Bangalore	648	3517	4.38
4	Mumbai	642	4159	4.34
5	Delhi	532	4691	3.60
6	Hyderabad	515	5206	3.48
7	Pune	461	5667	3.12
8	Mumbai Hub	300	5967	2.03
9	Kolkata	281	6248	1.90
10	Sonipat	275	6523	1.86
11	Chandigarh	258	6781	1.74
12	MAA	232	7013	1.57
13	Ahmedabad	204	7217	1.38
14	Chennai	194	7411	1.31
15	Del	172	7583	1.16

16	Jaipur	165	7748	1.12
17	FBD	159	7907	1.08
18	Muzaffrpur	159	8066	1.08
19	Ludhiana	157	8223	1.06
20	Kanpur	145	8368	0.98
21	Noida	129	8497	0.87
22	Chennai_Hub	123	8620	0.83
23	Jaipur_Hub	94	8714	0.64
24	Bhopal	85	8799	0.57
25	Surat	81	8880	0.55
26	HBR Layout PC	79	8959	0.53
27	Guwahati_Hub	75	9034	0.51
28	CCU	74	9108	0.50
29	Visakhapatnam	69	9177	0.47

In [129…

```
plt.figure(figsize=(18,14))
sns.barplot(data =df_source_city,
            y= df_source_city['source_city'],
            x= df_source_city['trip_uuid'])
plt.show()
```


Gurgaon
Bengaluru
Bhiwandi
Bangalore
Mumbai
Delhi
Hyderabad
Pune
Mumbai Hub
Kolkata
Sonipat
Chandigarh
MAA
Ahmedabad
Chennai
Del
Jaipur
FBD
Muzaffrpur
Ludhiana
Kanpur
Noida
Chennai_Hub
Jaipur_Hub
Bhopal
Surat
HBR Layout PC
Guwahati_Hub
CCU
Visakhapatnam
source_city
0
200
400
600
800
1000
trip_uuid

In [130…
```
df_source_place = df_aggid.groupby('source_place')['trip_uuid'].count().sort_values(ascending=False).to_frame().rese
df_source_place['Cummulative_sum']= df_source_place['trip_uuid'].cumsum()
df_source_place['Percentage']= np.round(df_source_place['trip_uuid']/ (df_source_place['trip_uuid'].sum())*100,2)
df_source_place = df_source_place[:30]
df_source_place
```

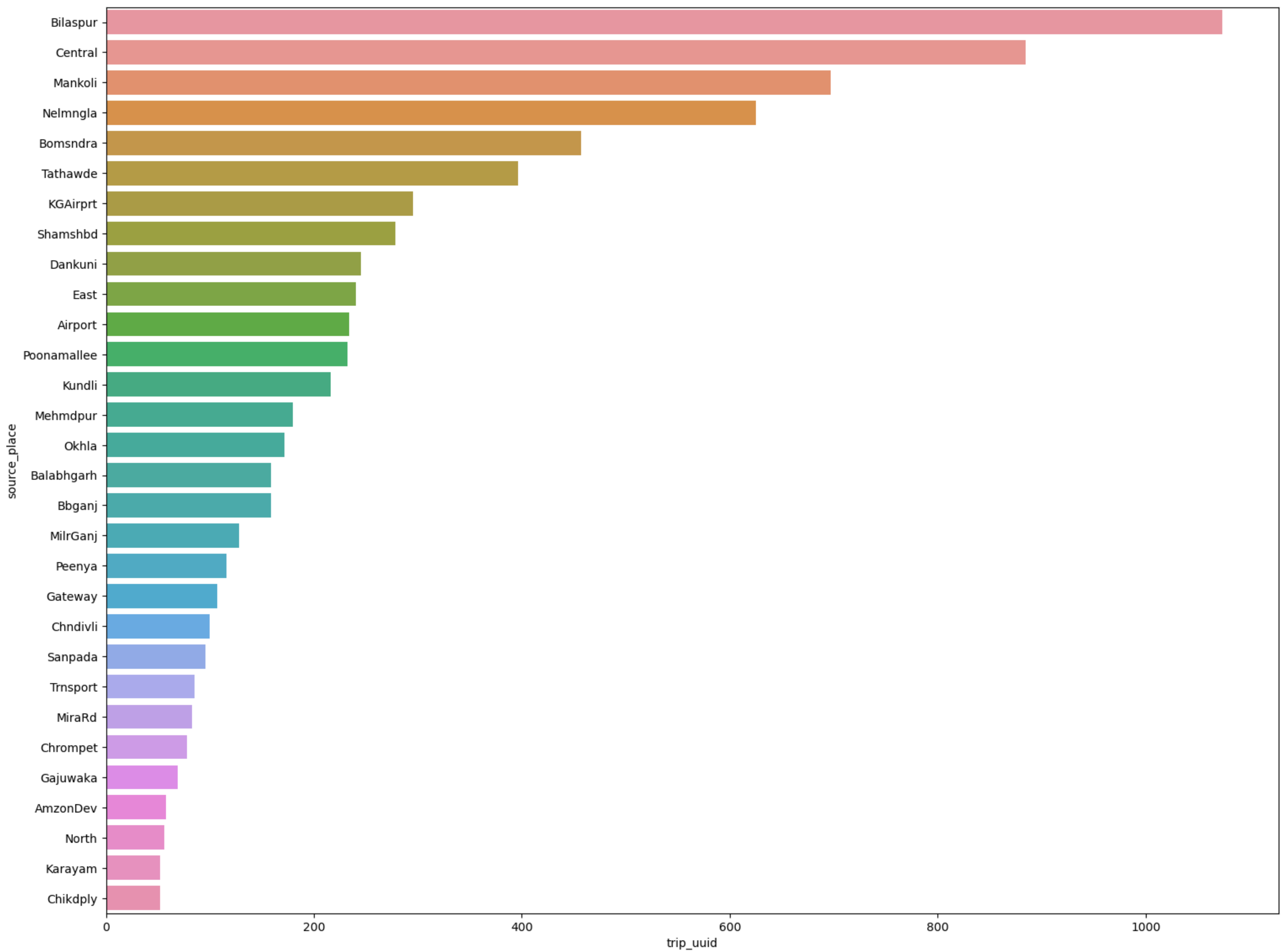
Out[130…

	source_place	trip_uuid	Cummulative_sum	Percentage
0	Bilaspur	1074	1074	8.34
1	Central	885	1959	6.87
2	Mankoli	697	2656	5.41
3	Nelmngla	625	3281	4.85
4	Bomsndra	457	3738	3.55
5	Tathawde	396	4134	3.08
6	KGAirprt	295	4429	2.29
7	Shamshbd	278	4707	2.16
8	Dankuni	245	4952	1.90
9	East	240	5192	1.86
10	Airport	234	5426	1.82
11	Poonamallee	232	5658	1.80
12	Kundli	216	5874	1.68
13	Mehmdpur	180	6054	1.40
14	Okhla	172	6226	1.34
15	Balabhgarh	159	6385	1.23

16	Bbganj	159	6544	1.23
17	MilrGanj	128	6672	0.99
18	Peenya	116	6788	0.90
19	Gateway	107	6895	0.83
20	Chndivli	100	6995	0.78
21	Sanpada	96	7091	0.75
22	Trnsport	85	7176	0.66
23	MiraRd	83	7259	0.64
24	Chrompet	78	7337	0.61
25	Gajuwaka	69	7406	0.54
26	AmzonDev	58	7464	0.45
27	North	56	7520	0.43
28	Karayam	52	7572	0.40
29	Chikdply	52	7624	0.40

In [131…

```
plt.figure(figsize=(18,14))
sns.barplot(data =df_source_place,
            y= df_source_place['source_place'],
            x= df_source_place['trip_uuid'])
plt.show()
```


Bilaspur
Central
Mankoli
Nelmngla
Bomsndra
Tathawde
KGAirprt
Shamshbd
Dankuni
East
Airport
Poonamallee
Kundli
Mehmdpur
Okhla
Balabhgarh
Bbganj
MilrGanj
Peenya
Gateway
Chndivli
Sanpada
Trnsport
MiraRd
Chrompet
Gajuwaka
AmzonDev
North
Karayam
Chikdply
source_place
0
200
400
600
800
1000
trip_uuid

In [132…

```python
df_source_code = df_aggid.groupby('source_code')['trip_uuid'].count().sort_values(ascending=False).to_frame().reset_
df_source_code['Cummulative_sum']= df_source_code['trip_uuid'].cumsum()
df_source_code['Percentage']= np.round(df_source_code['trip_uuid']/ (df_source_code['trip_uuid'].sum())*100,2)
df_source_code = df_source_code[:30]
df_source_code
```

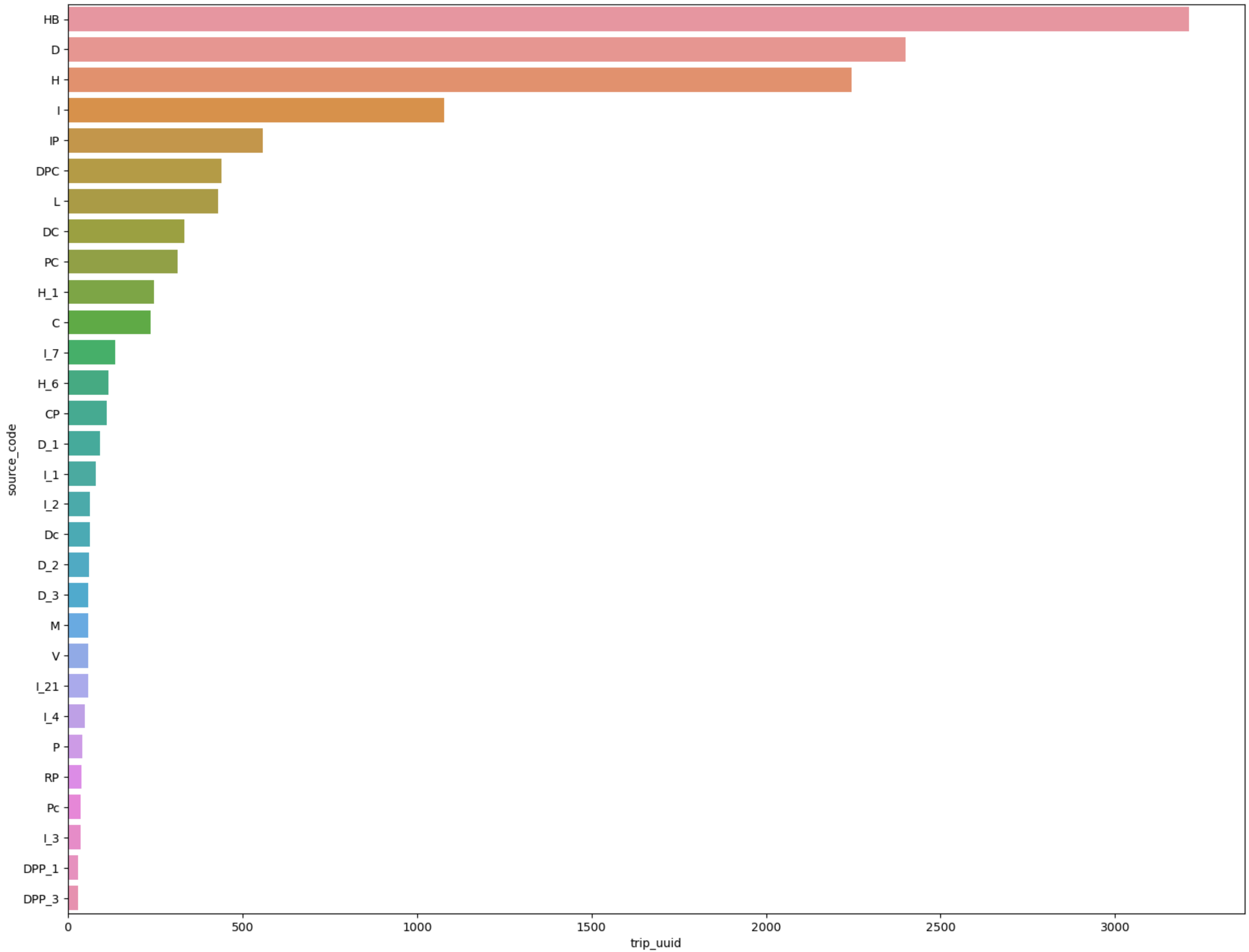
Out[132…

	source_code	trip_uuid	Cummulative_sum	Percentage
0	HB	3211	3211	24.94
1	D	2399	5610	18.63
2	H	2244	7854	17.43
3	I	1077	8931	8.37
4	IP	557	9488	4.33
5	DPC	439	9927	3.41
6	L	429	10356	3.33
7	DC	333	10689	2.59
8	PC	313	11002	2.43
9	H_1	247	11249	1.92
10	C	236	11485	1.83
11	I_7	135	11620	1.05
12	H_6	117	11737	0.91
13	CP	112	11849	0.87
14	D_1	91	11940	0.71
15	I_1	80	12020	0.62

16	I_2	62	12082	0.48
17	Dc	62	12144	0.48
18	D_2	60	12204	0.47
19	D_3	59	12263	0.46
20	M	58	12321	0.45
21	V	58	12379	0.45
22	I_21	57	12436	0.44
23	I_4	48	12484	0.37
24	P	40	12524	0.31
25	RP	39	12563	0.30
26	Pc	36	12599	0.28
27	I_3	36	12635	0.28
28	DPP_1	30	12665	0.23
29	DPP_3	28	12693	0.22

In [133…

```
plt.figure(figsize=(18,14))
sns.barplot(data =df_source_code,
            y= df_source_code['source_code'],
            x= df_source_code['trip_uuid'])
plt.show()
```



HB
D
H
I
IP
DPC
L
DC
PC
H_1
C
I_7
H_6
CP
D_1
I_1
I_2
Dc
D_2
D_3
M
V
I_21
I_4
P
RP
Pc
I_3
DPP_1
DPP_3
source_code
0
500
1000
1500
2000
2500
3000
trip_uuid

In [134…

```
df_dest_state = df_aggid.groupby('destination_state')['trip_uuid'].count().sort_values(ascending=False).to_frame().
df_dest_state['Cummulative_sum']= df_dest_state['trip_uuid'].cumsum()
df_dest_state['Percentage']= np.round(df_dest_state['trip_uuid']/ (df_dest_state['trip_uuid'].sum())*100,2)
# df_dest_state = df_dest_state[:30]
df_dest_state
```

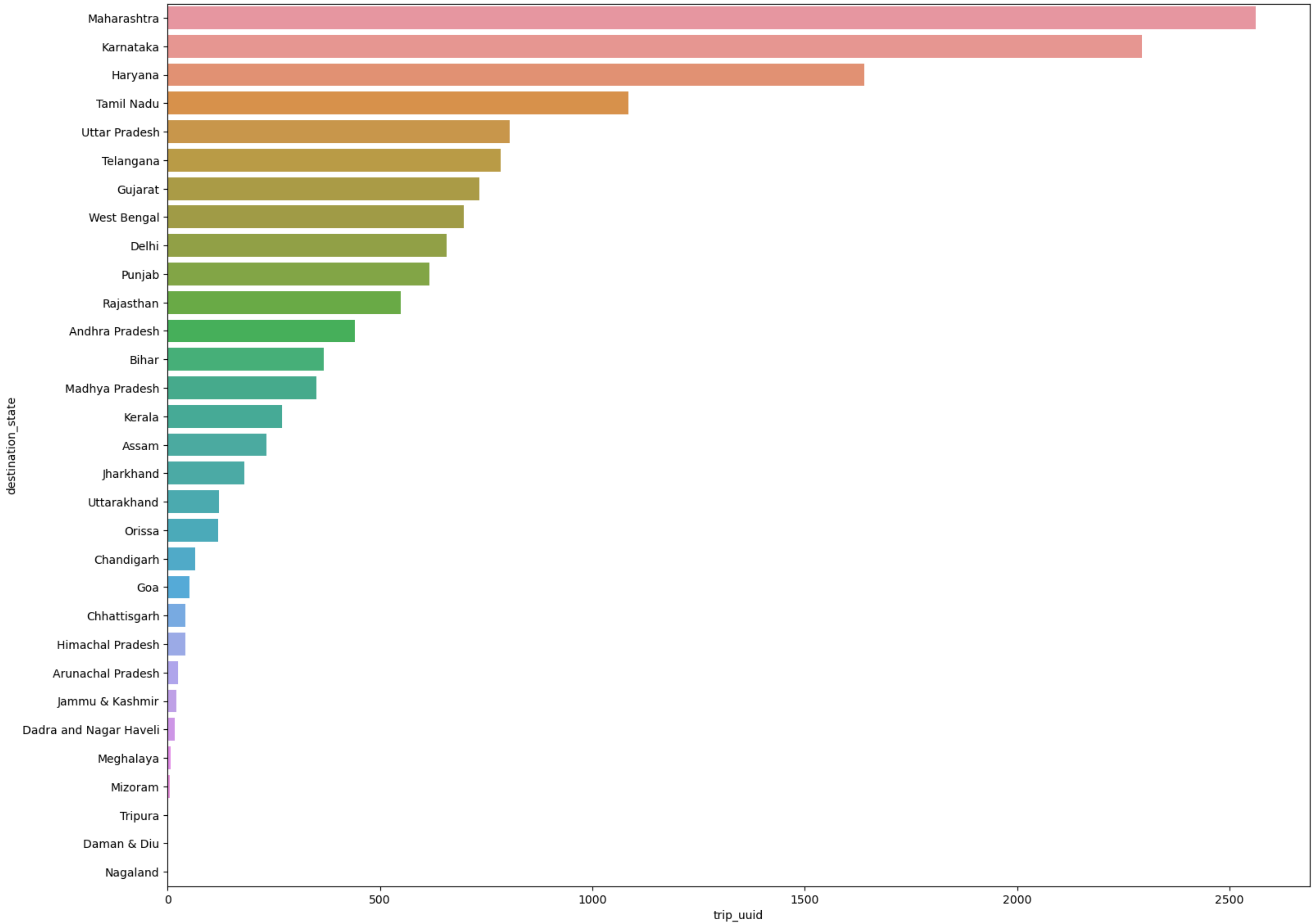
Out[134…

	destination_state	trip_uuid	Cummulative_sum	Percentage
0	Maharashtra	2561	2561	17.32
1	Karnataka	2294	4855	15.51
2	Haryana	1640	6495	11.09
3	Tamil Nadu	1084	7579	7.33
4	Uttar Pradesh	805	8384	5.44
5	Telangana	784	9168	5.30
6	Gujarat	734	9902	4.96
7	West Bengal	697	10599	4.71
8	Delhi	657	11256	4.44
9	Punjab	617	11873	4.17
10	Rajasthan	550	12423	3.72
11	Andhra Pradesh	442	12865	2.99
12	Bihar	367	13232	2.48
13	Madhya Pradesh	350	13582	2.37
14	Kerala	270	13852	1.83

15	Assam	232	14084	1.57
16	Jharkhand	181	14265	1.22
17	Uttarakhand	122	14387	0.83
18	Orissa	119	14506	0.80
19	Chandigarh	65	14571	0.44
20	Goa	52	14623	0.35
21	Chhattisgarh	43	14666	0.29
22	Himachal Pradesh	42	14708	0.28
23	Arunachal Pradesh	25	14733	0.17
24	Jammu & Kashmir	20	14753	0.14
25	Dadra and Nagar Haveli	17	14770	0.11
26	Meghalaya	8	14778	0.05
27	Mizoram	6	14784	0.04
28	Tripura	1	14785	0.01
29	Daman & Diu	1	14786	0.01
30	Nagaland	1	14787	0.01

In [135…

```
plt.figure(figsize=(18,14))
sns.barplot(data =df_dest_state,
            y= df_dest_state['destination_state'],
            x= df_dest_state['trip_uuid'])
plt.show()
```


Maharashtra
Karnataka
Haryana
Tamil Nadu
Uttar Pradesh
Telangana
Gujarat
West Bengal
Delhi
Punjab
Rajasthan
Andhra Pradesh
Bihar
Madhya Pradesh
Kerala
Assam
Jharkhand
Uttarakhand
Orissa
Chandigarh
Goa
Chhattisgarh
Himachal Pradesh
Arunachal Pradesh
Jammu & Kashmir
Dadra and Nagar Haveli
Meghalaya
Mizoram
Tripura
Daman & Diu
Nagaland
destination_state
0
500
1000
1500
2000
2500
trip_uuid

In [136…

```
df_dest_city = df_aggid.groupby('destination_city')['trip_uuid'].count().sort_values(ascending=False).to_frame().re
df_dest_city['Cummulative_sum']= df_dest_city['trip_uuid'].cumsum()
df_dest_city['Percentage']= np.round(df_dest_city['trip_uuid']/ (df_dest_city['trip_uuid'].sum())*100,2)
df_dest_city = df_dest_city[:30]
df_dest_city
```

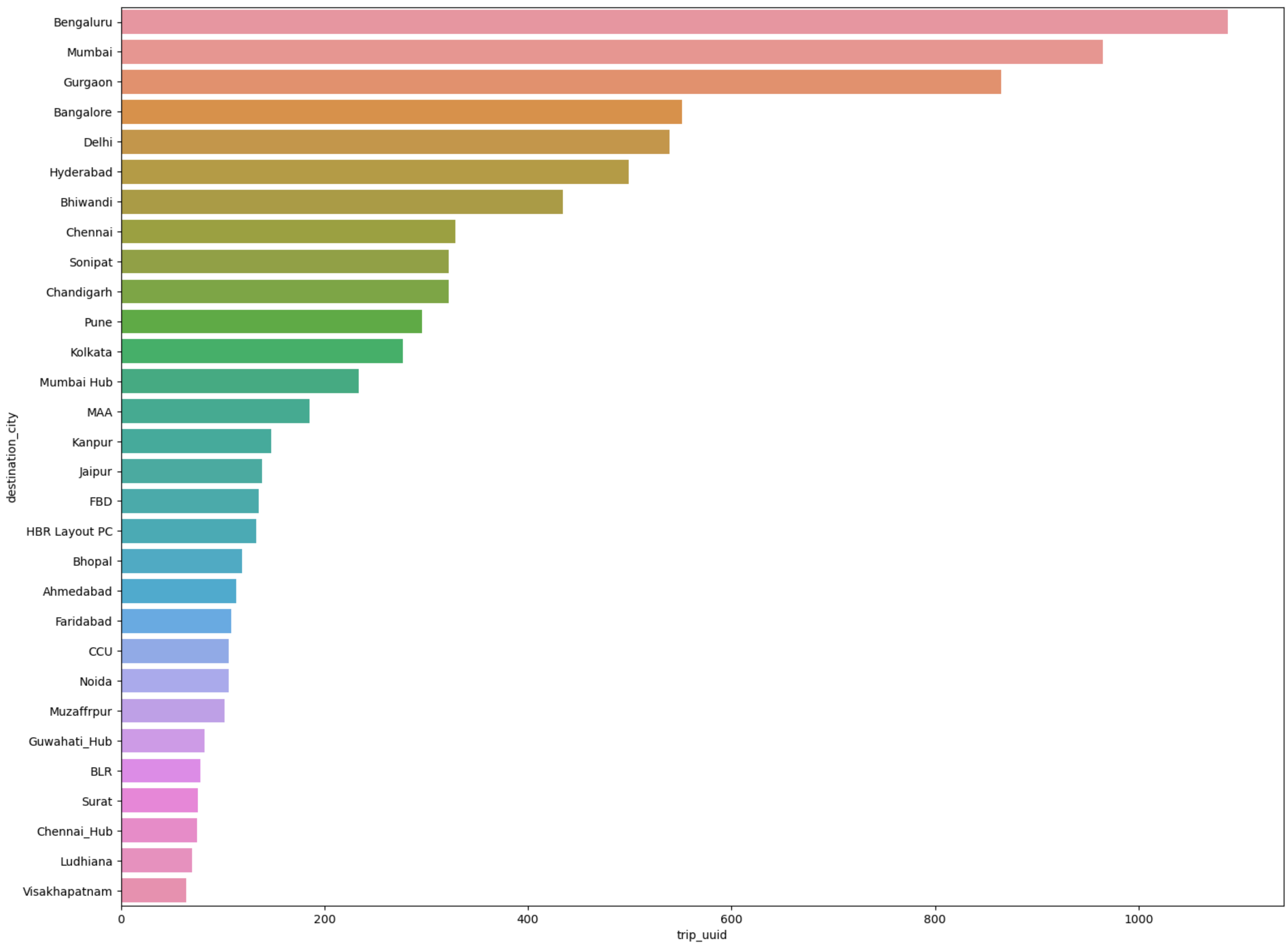
Out[136…

	destination_city	trip_uuid	Cummulative_sum	Percentage
0	Bengaluru	1088	1088	7.36
1	Mumbai	965	2053	6.53
2	Gurgaon	865	2918	5.85
3	Bangalore	551	3469	3.73
4	Delhi	539	4008	3.65
5	Hyderabad	499	4507	3.37
6	Bhiwandi	434	4941	2.94
7	Chennai	329	5270	2.22
8	Sonipat	322	5592	2.18
9	Chandigarh	322	5914	2.18
10	Pune	296	6210	2.00
11	Kolkata	277	6487	1.87
12	Mumbai Hub	234	6721	1.58
13	MAA	185	6906	1.25
14	Kanpur	148	7054	1.00
15	Jaipur	139	7193	0.94

16	FBD	135	7328	0.91
17	HBR Layout PC	133	7461	0.90
18	Bhopal	119	7580	0.80
19	Ahmedabad	113	7693	0.76
20	Faridabad	108	7801	0.73
21	CCU	106	7907	0.72
22	Noida	106	8013	0.72
23	Muzaffrpur	102	8115	0.69
24	Guwahati_Hub	82	8197	0.55
25	BLR	78	8275	0.53
26	Surat	76	8351	0.51
27	Chennai_Hub	75	8426	0.51
28	Ludhiana	70	8496	0.47
29	Visakhapatnam	64	8560	0.43

In [137…

```
plt.figure(figsize=(18,14))
sns.barplot(data =df_dest_city,
            y= df_dest_city['destination_city'],
            x= df_dest_city['trip_uuid'])
plt.show()
```


Bengaluru
Mumbai
Gurgaon
Bangalore
Delhi
Hyderabad
Bhiwandi
Chennai
Sonipat
Chandigarh
Pune
Kolkata
Mumbai Hub
MAA
Kanpur
Jaipur
FBD
HBR Layout PC
Bhopal
Ahmedabad
Faridabad
CCU
Noida
Muzaffrpur
Guwahati_Hub
BLR
Surat
Chennai_Hub
Ludhiana
Visakhapatnam
destination_city
0
200
400
600
800
1000
trip_uuid

In [138…

```
df_dest_place = df_aggid.groupby('destination_place')['trip_uuid'].count().sort_values(ascending=False).to_frame().
df_dest_place['Cummulative_sum']= df_dest_place['trip_uuid'].cumsum()
df_dest_place['Percentage']= np.round(df_dest_place['trip_uuid']/ (df_dest_place['trip_uuid'].sum())*100,2)
df_dest_place = df_dest_place[:25]
df_dest_place
```

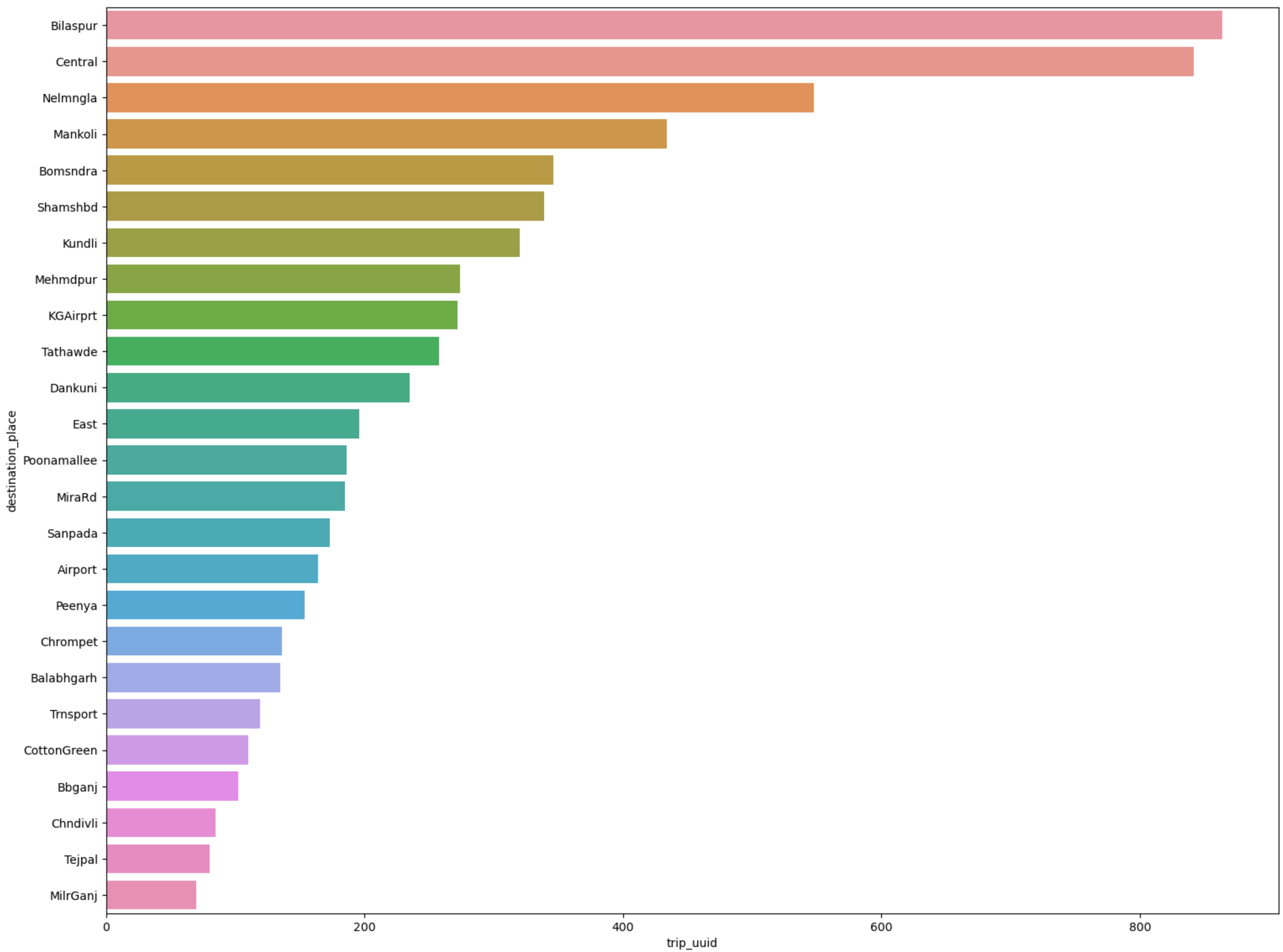
Out[138…

	destination_place	trip_uuid	Cummulative_sum	Percentage
0	Bilaspur	864	864	6.75
1	Central	842	1706	6.58
2	Nelmngla	548	2254	4.28
3	Mankoli	434	2688	3.39
4	Bomsndra	346	3034	2.70
5	Shamshbd	339	3373	2.65
6	Kundli	320	3693	2.50
7	Mehmdpur	274	3967	2.14
8	KGAirprt	272	4239	2.13
9	Tathawde	258	4497	2.02
10	Dankuni	235	4732	1.84
11	East	196	4928	1.53
12	Poonamallee	186	5114	1.45
13	MiraRd	185	5299	1.45
14	Sanpada	173	5472	1.35
15	Airport	164	5636	1.28

16	Peenya	154	5790	1.20
17	Chrompet	136	5926	1.06
18	Balabhgarh	135	6061	1.06
19	Trnsport	119	6180	0.93
20	CottonGreen	110	6290	0.86
21	Bbganj	102	6392	0.80
22	Chndivli	85	6477	0.66
23	Tejpal	80	6557	0.63
24	MilrGanj	70	6627	0.55

In [139…

```
plt.figure(figsize=(18,14))
sns.barplot(data =df_dest_place,
            y= df_dest_place['destination_place'],
            x= df_dest_place['trip_uuid'])
plt.show()
```



Bilaspur
Central
Nelmngla
Mankoli
Bomsndra
Shamshbd
Kundli
Mehmdpur
KGAirprt
Tathawde
Dankuni
East
Poonamallee
MiraRd
Sanpada
Airport
Peenya
Chrompet
Balabhgarh
Trnsport
CottonGreen
Bbganj
Chndivli
Tejpal
MilrGanj
destination_place
0
200
400
600
800
trip_uuid

In [140…

```
df_dest_code = df_aggid.groupby('destination_code')['trip_uuid'].count().sort_values(ascending=False).to_frame().re
df_dest_code['Cummulative_sum']= df_dest_code['trip_uuid'].cumsum()
df_dest_code['Percentage']= np.round(df_dest_code['trip_uuid']/ (df_dest_code['trip_uuid'].sum())*100,2)
df_dest_code = df_dest_code[:30]
df_dest_code
```

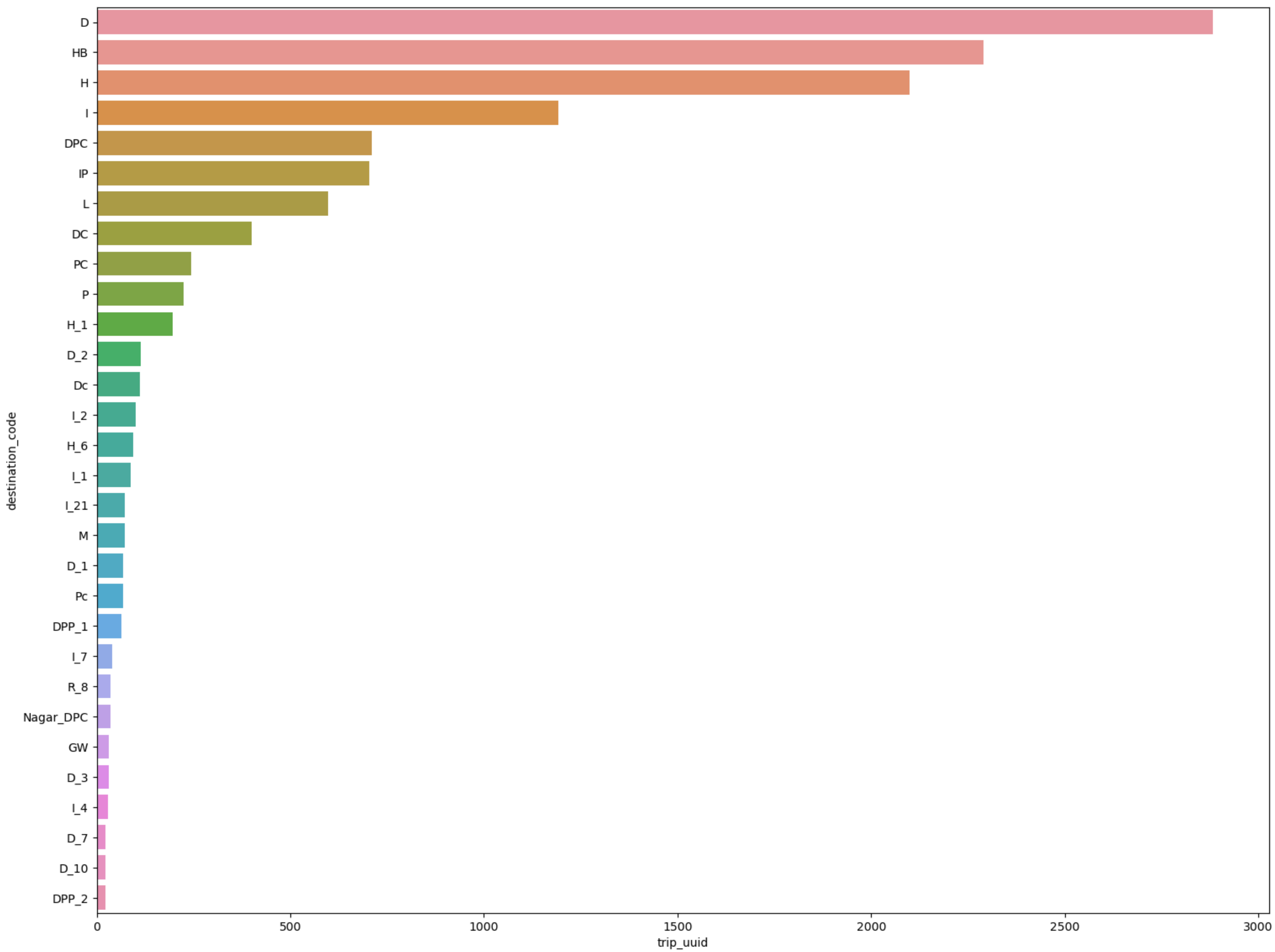
Out[140…

	destination_code	trip_uuid	Cummulative_sum	Percentage
0	D	2883	2883	22.53
1	HB	2290	5173	17.90
2	H	2100	7273	16.41
3	I	1192	8465	9.32
4	DPC	710	9175	5.55
5	IP	704	9879	5.50
6	L	597	10476	4.67
7	DC	401	10877	3.13
8	PC	243	11120	1.90
9	P	224	11344	1.75
10	H_1	197	11541	1.54
11	D_2	113	11654	0.88
12	Dc	111	11765	0.87
13	I_2	101	11866	0.79
14	H_6	95	11961	0.74
15	I_1	87	12048	0.68

16	I_21	73	12121	0.57
17	M	72	12193	0.56
18	D_1	69	12262	0.54
19	Pc	69	12331	0.54
20	DPP_1	64	12395	0.50
21	I_7	40	12435	0.31
22	R_8	36	12471	0.28
23	Nagar_DPC	36	12507	0.28
24	GW	31	12538	0.24
25	D_3	31	12569	0.24
26	I_4	30	12599	0.23
27	D_7	22	12621	0.17
28	D_10	22	12643	0.17
29	DPP_2	22	12665	0.17

In [141…

```
plt.figure(figsize=(18,14))
sns.barplot(data =df_dest_code,
            y= df_dest_code['destination_code'],
            x= df_dest_code['trip_uuid'])
plt.show()
```



D
HB
H
I
DPC
IP
L
DC
PC
P
H_1
D_2
Dc
I_2
H_6
I_1
I_21
M
D_1
Pc
DPP_1
I_7
R_8
Nagar_DPC
GW
D_3
I_4
D_7
D_10
DPP_2
destination_code
0
500
1000
1500
2000
2500
3000
trip_uuid

In [142…

```
num_cols = df_aggid[['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']]
num_cols.isnull().sum()
```

Out[142…

```
od_total_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
```

In [143…

```
df_corr = num_cols.corr()
df_corr
```

Out[143…

	od_total_time	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	seg
od_total_time	1.000000	0.999999	0.919074	0.961560	0.927416	0.925126	
start_scan_to_end_scan	0.999999	1.000000	0.919159	0.961612	0.927471	0.925205	
actual_distance_to_destination	0.919074	0.919159	1.000000	0.953920	0.993568	0.997268	
actual_time	0.961560	0.961612	0.953920	1.000000	0.958781	0.959398	
osrm_time	0.927416	0.927471	0.993568	0.958781	1.000000	0.997588	
osrm_distance	0.925126	0.925205	0.997268	0.959398	0.997588	1.000000	

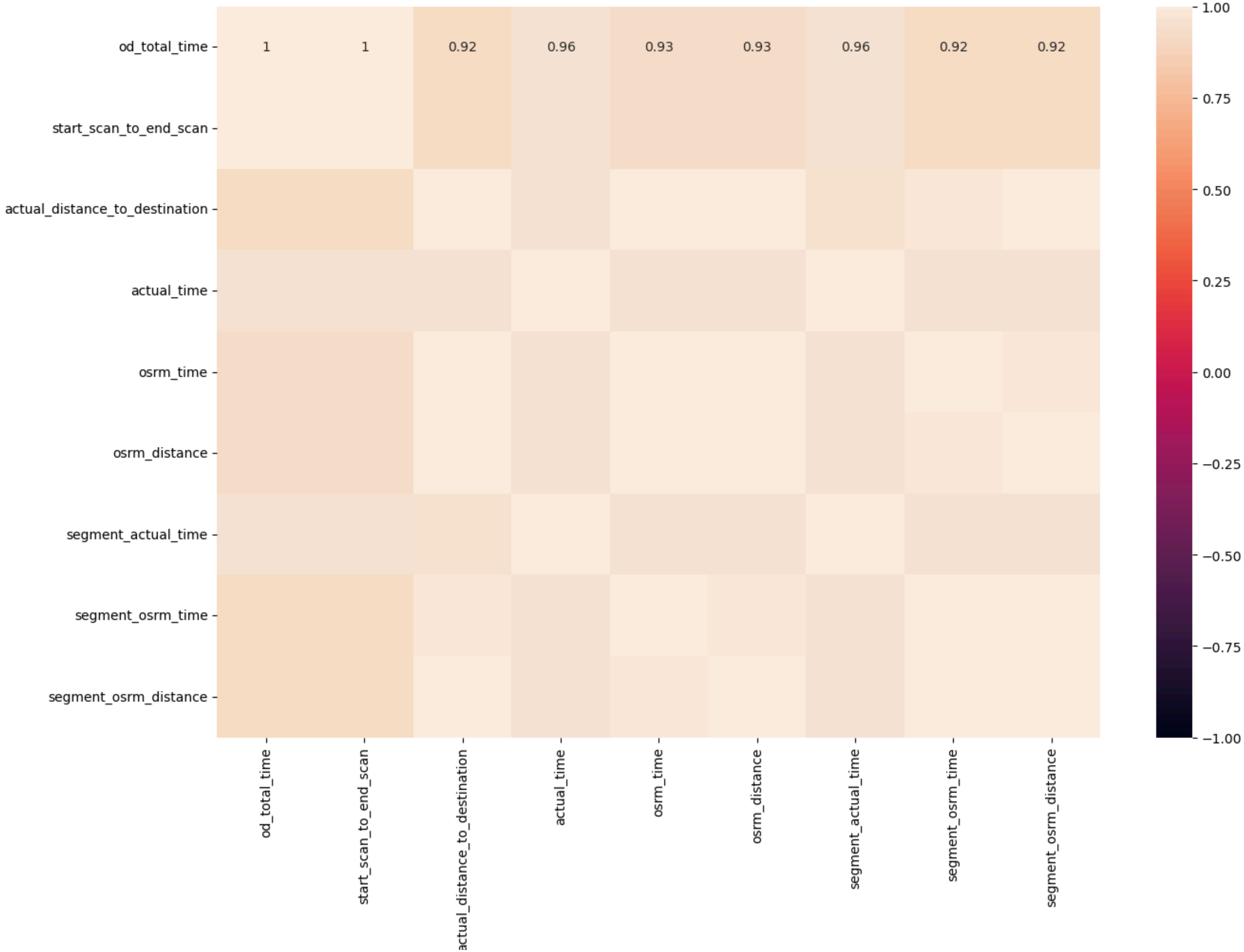
segment_actual_time	0.961582	0.961634	0.952987	0.999989	0.957955	0.958540
segment_osrm_time	0.919358	0.919429	0.987542	0.954044	0.993263	0.991802
segment_osrm_distance	0.920099	0.920191	0.993068	0.957151	0.991624	0.994712

In [144…

```
plt.figure(figsize = (15, 10))
sns.heatmap(data = df_corr, vmin = -1, vmax = 1, annot = True)
plt.plot()
```

Out[144…

```
[]
```


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
1
1
0.92
0.96
0.93
0.93
0.96
0.92
0.92
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

📊 Dataset Insights Summary

🚚 Route Type Distribution

- The dataset contains two route types:
  - **Carting**: ~60%
  - **FTL (Full Truck Load)**: ~39%

📆 Month-wise Distribution

- **September** contributes the majority of the data: **~88%**
- **October** contributes the remaining: **~12%**

🗓️ Day-wise Trends

- Most orders were placed in the **2nd and 3rd weeks** of the month.
- The **highest number of orders** occurred on the **21st** of the month.
- The **lowest number of orders** occurred on the **31st**.

📅 Week-wise Distribution

- The dataset includes data from **Weeks 37 to 40**.
  - **Week 38**: ~34%
  - **Week 39**: ~30%
  - **Week 37**: ~24%
  - **Week 40**: ~12%

🗺️ Source State Distribution

- **Top contributing states** (~57.5% combined):
  - Maharashtra, Karnataka, Haryana, Tamil Nadu, Telangana
- **Least contributing states** (~0.27% combined):

- Dadra and Nagar Haveli, Pondicherry, Nagaland, Mizoram, Arunachal Pradesh

⚠️ These are mostly **eastern states and union territories**, possibly affected by **connectivity issues**.

🏙️ Top Source Cities

- Major source cities (Tier-I) contributing ~28.11%:
  - Gurgaon, Bengaluru, Bhiwandi, Bangalore, Mumbai

🎯 Destination State Distribution

- **Top 5 destination states** (~56.69% combined):
  - Karnataka, Haryana, Tamil Nadu, Uttar Pradesh, and one more (you might want to list it explicitly).
- **Lowest contributing states**:
  - Meghalaya, Mizoram, Tripura, Daman & Diu, Nagaland

📈 Business Insights from Dataset & EDA

1. Route Optimization & Fleet Management

- **Carting dominates the dataset (60%)**, suggesting frequent smaller shipments. Optimize routing and scheduling for carting operations to improve efficiency and reduce costs.
- **FTL accounts for 39%**: Larger shipments might need better coordination or fewer trips. Evaluate if underutilized FTL trips can be consolidated or re-routed.

---

2. Seasonal & Weekly Demand Patterns

- **September alone contributes 88% of the data.**
  - September could be a seasonal demand peak—possibly linked to festivals or quarter-end cycles.
  - Prepare additional resources (fleet, manpower) in August to meet expected September surge.

- **Highest order volume occurs mid-month (especially around the 21st).**
    - Mid-month might need dynamic capacity scaling or shift planning.
- **Week 38 is peak (34%), Week 40 is the lowest (12%)**
    - Using this insight for *demand forecasting* and shift planning.

---

3. Geographical Distribution – Market Penetration

- **Top source states (Maharashtra, Karnataka, Haryana, etc.) account for 57.5%**.
    - Strengthen infrastructure in these key states.
- **Low-contribution states (e.g., Mizoram, Pondicherry) are mostly from Eastern regions or union territories.**
    - Low market presence may be due to poor connectivity. Consider infrastructure development or partnerships if expansion is desired.

---

4. City-Level Operational Insight

- **Tier-I cities (e.g., Bangalore, Gurgaon, Mumbai) contribute over 28% of dispatches**.
    - Focus on performance KPIs in these cities—delays, service quality, and customer satisfaction will have a wider impact.

---

5. Data Distribution & Cleaning Needs

- **Right-skewed distributions** and **prevalent outliers**, especially in `actual_time` and `segment_actual_time`, signal potential data quality issues.
    - *Operational Risk:* Delivery time estimations could be skewed.
    - *Recommendation:* Apply IQR-based outlier treatment and consider transforming data for model reliability.

---

6. Distance & Time Inconsistencies

- Mann-Whitney U Tests showed significant differences between:
    - `osrm_time` vs `segment_osrm_time`

- `osrm_distance` vs `segment_osrm_distance`
- `actual_time` vs `segment_actual_time`
- 👉 *Conclusion:* There may be aggregation errors or inconsistencies between segment-level and total trip data.
- *Action:* Audit your route segmentation and tracking systems to ensure data integrity.

Recommendations

- The OSRM trip planning system needs to be improved. Discrepancies need to be catered to for transporters, if the routing engine is configured for optimum results.

- osrm_time and actual_time are different. Team needs to make sure this difference is reduced, so that better delivery time prediction can be made and it becomes convenient for the customer to expect an accurate delivery time.

- The osrm distance and actual distance covered are also not same i.e. maybe the delivery person is not following the predefined route which may lead to late deliveries or the osrm devices is not properly predicting the route based on distance, traffic and other factors. Team needs to look into it.

- Most of the orders are coming from/reaching to states like Maharashtra, Karnataka, Haryana and Tamil Nadu. The existing corridors can be further enhanced to improve the penetration in these areas.

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

- From state point of view, we might have very heavy traffic in certain states and bad terrain conditions in certain states. This will be a good indicator to plan and cater to demand during peak festival seasons.
