Delhivery Business Case Study - Feature Engineering

About Delhivery:

Delhivery is the largest and fastest-growing fully integrated player in India by revenue in Fiscal 2021. They aim to build the operating system for commerce, through a combination of world-class infrastructure, logistics operations of the highest quality, and cutting-edge engineering and technology capabilities.

Business Problem:

1. **The Data team builds intelligence and capabilities using this data that helps them to widen the gap between the quality, efficiency, and profitability of their business versus their competitors.**

2. **The company wants to understand and process the data coming out of data engineering pipelines:**
   - Clean, sanitize and manipulate data to get useful features out of raw fields
   - Make sense out of the raw data and help the data science team to build forecasting models on it

Solution Approach:

1. **Basic Data Cleaning and Perform Exploratory Data Analysis (EDA).**
2. **Build some features to prepare the data for actual analysis. Extract features from the below fields.**
3. **In-depth analysis and feature engineering.**
4. **Insights.**
5. **Business Recommendations.**

Dataset:

The company collected the data of customers who used their services.

Dataset Link: delhivery_data.csv

`Column Profiling:`

- **data:** Tells whether the data is testing or training data
- **trip_creation_time:** Timestamp of trip creation
- **route_schedule_uuid:** Unique Id for a particular route schedule
- **route_type:** Transportation type
- **FTL (Full Truck Load):** FTL shipments get to the destination sooner, as the truck is making no other pickups or drop-offs along the way
- **Carting:** Handling system consisting of small vehicles (carts)
- **trip_uuid:** Unique ID given to a particular trip (A trip may include different source and destination centers)
- **source_center:** Source ID of trip origin
- **source_name:** Source Name of trip origin
- **destination_cente:** Destination ID

- **destination_name:** Destination Name
- **od_start_time:** Trip start time
- **od_end_time:** Trip end time
- **start_scan_to_end_scan:** Time taken to deliver from source to destination
- **is_cutoff:** Unknown field
- **cutoff_factor:** Unknown field
- **cutoff_timestamp:** Unknown field
- **actual_distance_to_destination:** Distance in Kms between source and destination warehouse
- **actual_time:** Actual time taken to complete the delivery (Cumulative)
- **osrm_time:** An open-source routing engine time calculator which computes the shortest path between points in a given map (Includes usual traffic, distance through major and minor roads) and gives the time (Cumulative)
- **osrm_distance – An open-source routing engine which computes the shortest path between points in a given map (Includes usual traffic, distance through major and minor roads) (Cumulative)**
- **factor – Unknown field**
- **segment_actual_time:** This is a segment time. Time taken by the subset of the package delivery
- **segment_osrm_time:** This is the OSRM segment time. Time taken by the subset of the package delivery
- **segment_osrm_distance:** This is the OSRM distance. Distance covered by subset of the package delivery
- **segment_factor:** Unknown field

Importing Libraries:

In [1]:
```
import pandas as pd    # data processing, CSV file I/O (e.g. pd.read_csv)
import numpy as np    # linear algebra
import seaborn as sns    # data visualization
import matplotlib as mpl    # data visualization
import matplotlib.pyplot as plt    # data visualization
import plotly.graph_objects as go    # data visualization
import plotly.express as px    # data visualization
import scipy.stats as spy    # statistical analysis
from scipy.special import comb    # statistical analysis
from scipy.stats import binom, norm, t, poisson, expon, geom    # statistical analysis
from scipy.stats import ttest_1samp, ttest_ind, ttest_ind_from_stats, boxcox    # statistical analysis
from scipy.stats import shapiro, levene, kruskal, chi2, chi2_contingency, pearsonr, spearmanr    # statistical analysis
from statsmodels.graphics.gofplots import qqplot    # statistical analysis
from sklearn.preprocessing import LabelEncoder, StandardScaler, MinMaxScaler, OneHotEncoder    # statistical analysis
import warnings
warnings.simplefilter('ignore')
%matplotlib inline

# !pip install pySankey --quiet
from pySankey.sankey import sankey    # data visualization
```

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1. Basic Data Cleaning and Perform Exploratory Data Analysis (EDA):

A. Analyze structure and characteristics of the dataset.
B. Converting time columns into pandas datetime.
C. Handle missing values in the data.

1A. Analyze structure and characteristics of the dataset:

Reading the Dataset:

In [2]:
```
df = pd.read_csv("delhivery_data.csv")
```

Looking at the dataset:

In [3]:
```
df.head()
```

Out[3]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	c
0	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khamb
1	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khamb
2	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khamb
3	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khamb
4	training	2018-09-20 02:35:36.476840	thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...	Carting	trip-153741093647649320	IND388121AAA	Anand_VUNagar_DC (Gujarat)	IND388620AAB	Khamb

5 rows × 24 columns

In [4]:
```
df.tail()
```

Out[4]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center	d
144862	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurg
144863	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurg
144864	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurg
144865	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurg
144866	training	2018-09-20 16:24:28.436231	thanos::sroute:f0569d2f-4e20-4c31-8542-67b86d5...	Carting	trip-153746066843555182	IND131028AAB	Sonipat_Kundli_H (Haryana)	IND000000ACB	Gurg

5 rows × 24 columns

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

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

In [6]:
```
print(f"# rows: {df.shape[0]} \n# columns: {df.shape[1]}")
```

```
# rows: 144867
# columns: 24
```

Columns in the Dataset:

In [7]:
```
df.columns
```

Out[7]:
```
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')
```

Datatype of the columns:

In [8]:
```
df.dtypes
```

Out[8]:
```
data                              object
trip_creation_time                object
route_schedule_uuid               object
route_type                        object
trip_uuid                         object
source_center                     object
source_name                       object
destination_center                object
destination_name                  object
od_start_time                     object
od_end_time                       object
start_scan_to_end_scan           float64
is_cutoff                           bool
cutoff_factor                      int64
cutoff_timestamp                  object
actual_distance_to_destination   float64
actual_time                      float64
osrm_time                        float64
osrm_distance                    float64
factor                           float64
segment_actual_time              float64
segment_osrm_time                float64
segment_osrm_distance            float64
segment_factor                   float64
dtype: object
```

Basic information about the dataset:

In [9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 24 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   data                            144867 non-null  object 
 1   trip_creation_time              144867 non-null  object 
 2   route_schedule_uuid             144867 non-null  object 
 3   route_type                      144867 non-null  object 
 4   trip_uuid                       144867 non-null  object 
 5   source_center                   144867 non-null  object 
 6   source_name                     144574 non-null  object 
 7   destination_center              144867 non-null  object 
 8   destination_name                144606 non-null  object 
 9   od_start_time                   144867 non-null  object 
 10  od_end_time                     144867 non-null  object 
 11  start_scan_to_end_scan          144867 non-null  float64
 12  is_cutoff                       144867 non-null  bool   
 13  cutoff_factor                   144867 non-null  int64  
 14  cutoff_timestamp                144867 non-null  object 
 15  actual_distance_to_destination  144867 non-null  float64
 16  actual_time                     144867 non-null  float64
 17  osrm_time                       144867 non-null  float64
 18  osrm_distance                   144867 non-null  float64
 19  factor                          144867 non-null  float64
 20  segment_actual_time             144867 non-null  float64
 21  segment_osrm_time               144867 non-null  float64
 22  segment_osrm_distance           144867 non-null  float64
 23  segment_factor                  144867 non-null  float64
dtypes: bool(1), float64(10), int64(1), object(12)
memory usage: 25.6+ MB
```

Basic statistical information about the dataset:

In [10]:
```
df.describe().T
```

Out[10]:

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

In [11]:
```
df.describe(include = 'object').T
```

Out[11]:

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

Time period for which the data is given:

In [12]:
```
df['trip_creation_time'].min(), df['od_end_time'].max()
```

Out[12]:
```
('2018-09-12 00:00:16.535741', '2018-10-08 03:00:24.353479')
```

1B. Converting time columns into pandas datetime:

In [13]:
```
datetime_columns = ['trip_creation_time', 'od_start_time', 'od_end_time']
for i in datetime_columns:
    df[i] = pd.to_datetime(df[i])
```

In [14]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144867 entries, 0 to 144866
Data columns (total 24 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   data                            144867 non-null  object
 1   trip_creation_time              144867 non-null  datetime64[ns]
 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  datetime64[ns]
 10  od_end_time                     144867 non-null  datetime64[ns]
 11  start_scan_to_end_scan          144867 non-null  float64
 12  is_cutoff                       144867 non-null  bool
 13  cutoff_factor                   144867 non-null  int64
 14  cutoff_timestamp                144867 non-null  object
 15  actual_distance_to_destination  144867 non-null  float64
 16  actual_time                     144867 non-null  float64
 17  osrm_time                       144867 non-null  float64
 18  osrm_distance                   144867 non-null  float64
 19  factor                          144867 non-null  float64
 20  segment_actual_time             144867 non-null  float64
 21  segment_osrm_time               144867 non-null  float64
 22  segment_osrm_distance           144867 non-null  float64
 23  segment_factor                  144867 non-null  float64
dtypes: bool(1), datetime64[ns](3), float64(10), int64(1), object(9)
memory usage: 25.6+ MB
```

1B. Handling missing values in the data:

Dropping unknown fields:

In [15]:
```
unknown_fields = ['is_cutoff', 'cutoff_factor', 'cutoff_timestamp', 'factor', 'segment_factor']
df = df.drop(columns = unknown_fields)
```

Unique entries present in each column:

In [16]:
```
for i in df.columns:
    print(f"Unique entries for column {i:<30} = {df[i].nunique()}")
```

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

For all those columns where number of unique entries is 2, converting the datatype of columns to category:

In [17]:
```
df['data'] = df['data'].astype('category')
df['route_type'] = df['route_type'].astype('category')
```

In [18]:
```
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
```

Finding null values present in the dataset:

In [19]:
```
np.any(df.isnull())
```

Out[19]:
```
True
```

In [20]:
```
df.isnull().sum()
```

Out[20]:
```
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 [21]:
```
missing_source_name = df.loc[df['source_name'].isnull(), 'source_center'].unique()
missing_source_name
```

Out[21]:
```
array(['IND342902A1B', 'IND577116AAA', 'IND282002AAD', 'IND465333A1B',
       'IND841301AAC', 'IND509103AAC', 'IND126116AAA', 'IND331022A1B',
       'IND505326AAB', 'IND852118A1B'], dtype=object)
```

In [22]:
```
missing_destination_name  = df.loc[df['destination_name'].isnull(), 'destination_center'].unique()
missing_destination_name
```

Out[22]:
```
array(['IND342902A1B', 'IND577116AAA', 'IND282002AAD', 'IND465333A1B',
       'IND841301AAC', 'IND505326AAB', 'IND852118A1B', 'IND126116AAA',
       'IND509103AAC', 'IND221005A1A', 'IND250002AAC', 'IND331001A1C',
       'IND122015AAC'], dtype=object)
```

In [23]:
```
for i in missing_source_name:
    unique_source_name = df.loc[df['source_center'] == i, 'source_name'].unique()
    if pd.isna(unique_source_name):
        print("Source Center :", i, "-" * 10, "Source Name :", 'Not Found')
    else :
        print("Source Center :", i, "-" * 10, "Source Name :", unique_source_name)
```

```
Source Center : IND342902A1B ---------- Source Name : Not Found
Source Center : IND577116AAA ---------- Source Name : Not Found
Source Center : IND282002AAD ---------- Source Name : Not Found
Source Center : IND465333A1B ---------- Source Name : Not Found
Source Center : IND841301AAC ---------- Source Name : Not Found
Source Center : IND509103AAC ---------- Source Name : Not Found
Source Center : IND126116AAA ---------- Source Name : Not Found
Source Center : IND331022A1B ---------- Source Name : Not Found
Source Center : IND505326AAB ---------- Source Name : Not Found
Source Center : IND852118A1B ---------- Source Name : Not Found
```

In [24]:
```
for i in missing_source_name:
    unique_destination_name = df.loc[df['destination_center'] == i, 'destination_name'].unique()
    if (pd.isna(unique_source_name)) or (unique_source_name.size == 0):
        print("Destination Center :", i, "-" * 10, "Destination Name :", 'Not Found')
    else :
        print("Destination Center :", i, "-" * 10, "Destination Name :", unique_destination_name)
```

```
Destination Center : IND342902A1B ---------- Destination Name : Not Found
Destination Center : IND577116AAA ---------- Destination Name : Not Found
Destination Center : IND282002AAD ---------- Destination Name : Not Found
Destination Center : IND465333A1B ---------- Destination Name : Not Found
Destination Center : IND841301AAC ---------- Destination Name : Not Found
Destination Center : IND509103AAC ---------- Destination Name : Not Found
Destination Center : IND126116AAA ---------- Destination Name : Not Found
Destination Center : IND331022A1B ---------- Destination Name : Not Found
Destination Center : IND505326AAB ---------- Destination Name : Not Found
Destination Center : IND852118A1B ---------- Destination Name : Not Found
```

The IDs for which the source name is missing, are all those IDs for destination also missing?

In [25]:
```
np.all(df.loc[df['source_name'].isnull(), 'source_center'].isin(missing_destination_name))
```

Out[25]:
```
False
```

Treating missing destination names and source names:

In [26]:
```
count = 1
for i in missing_destination_name:
    df.loc[df['destination_center']==i, 'destination_name'] = df.loc[df['destination_center']==i, 'destination_name'].re
        np.nan, f'location_{count}')
    count += 1
```

In [27]:
```
d = {}
for i in missing_source_name:
    d[i] = df.loc[df['destination_center'] == i, 'destination_name'].unique()
    for idx, val in d.items():
        if len(val) == 0:
            d[idx] = [f'location_{count}']
            count += 1
d2 = {}
for idx, val in d.items():
    d2[idx] = val[0]
for i, v in d2.items():
    print(i, v)
```

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

In [28]:
```
for i in missing_source_name:
    df.loc[df['source_center'] == i, 'source_name'] = df.loc[df['source_center'] == i, 'source_name'].replace(np.nan, d2
```

In [29]:
```
df.isna().sum()
```

Out[29]:
```
data                             0
trip_creation_time               0
route_schedule_uuid              0
route_type                       0
trip_uuid                        0
source_center                    0
source_name                      0
destination_center               0
destination_name                 0
od_start_time                    0
od_end_time                      0
start_scan_to_end_scan           0
actual_distance_to_destination   0
actual_time                      0
osrm_time                        0
osrm_distance                    0
segment_actual_time              0
segment_osrm_time                0
segment_osrm_distance            0
dtype: int64
```

---

2. Build some features to prepare the data for actual analysis.

Extract features from the below fields:

A. Source Name: Split and extract features out of destination. City-place-code (State)
B. Destination Name: Split and extract features out of destination. City-place-code (State)
C. Trip_creation_time: Extract features like month, year and day etc

---

2A. Source Name: Split and extract features out of destination. City-place-code (State):

Merging of rows and aggregation of fields:

How to begin"

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

In [30]:
```
grouping_1 = ['trip_uuid', 'source_center', 'destination_center']
df1 = df.groupby(by = grouping_1, as_index = False).agg({'data' : 'first',
                                                         'route_type' : 'first',
                                                         'trip_creation_time' : 'first',
                                                         'source_name' : 'first',
                                                         'destination_name' : 'last',
                                                         'od_start_time' : 'first',
                                                         'od_end_time' : 'first',
                                                         'start_scan_to_end_scan' : 'first',
                                                         'actual_distance_to_destination' : 'last',
                                                         'actual_time' : 'last',
                                                         'osrm_time' : 'last',
                                                         'osrm_distance' : 'last',
                                                         'segment_actual_time' : 'sum',
                                                         'segment_osrm_time' : 'sum',
                                                         'segment_osrm_distance' : 'sum'})
df1
```

Out[30]:

	trip_uuid	source_center	destination_center	data	route_type	trip_creation_time	source_name	destination_na
0	trip-153671041653548748	IND209304AAA	IND000000ACB	training	FTL	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bilaspur_ (Harya
1	trip-153671041653548748	IND462022AAA	IND209304AAA	training	FTL	2018-09-12 00:00:16.535741	Bhopal_Trnsport_H (Madhya Pradesh)	Kanpur_Central_H_6 (U Prade
2	trip-153671042288605164	IND561203AAB	IND562101AAA	training	Carting	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_ShntiSg (Karnata
3	trip-153671042288605164	IND572101AAA	IND561203AAB	training	Carting	2018-09-12 00:00:22.886430	Tumkur_Veersagr_I (Karnataka)	Doddablpur_ChikaDPF (Karnata
4	trip-153671043369099517	IND000000ACB	IND160002AAC	training	FTL	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)	Chandigarh_Mehmdpu (Punj
...	...	...	...	...	...	...	...	...
26363	trip-153861115439069069	IND628204AAA	IND627657AAA	test	Carting	2018-10-03 23:59:14.390954	Tirchchndr_Shnmgprm_D (Tamil Nadu)	Thisayanvilai_UdnkdiRD (Tamil Na
26364	trip-153861115439069069	IND628613AAA	IND627005AAA	test	Carting	2018-10-03 23:59:14.390954	Peikulam_SriVnktpm_D (Tamil Nadu)	Tirunelveli_VdkkuS (Tamil Na
26365	trip-153861115439069069	IND628801AAA	IND628204AAA	test	Carting	2018-10-03 23:59:14.390954	Eral_Busstand_D (Tamil Nadu)	Tirchchndr_Shnmgprr (Tamil Na
26366	trip-153861118270144424	IND583119AAA	IND583101AAA	test	FTL	2018-10-03 23:59:42.701692	Sandur_WrdN1DPP_D (Karnataka)	Bellary_Dc (Karnata
26367	trip-153861118270144424	IND583201AAA	IND583119AAA	test	FTL	2018-10-03 23:59:42.701692	Hospet (Karnataka)	Sandur_WrdN1DPF (Karnata

26368 rows × 18 columns

Calculating the time taken between od_start_time and od_end_time and keeping it as a feature.

Droping the original columns, if required:

In [31]:
```
df1['od_total_time'] = df1['od_end_time'] - df1['od_start_time']
df1.drop(columns = ['od_end_time', 'od_start_time'], inplace = True)
df1['od_total_time'] = df1['od_total_time'].apply(lambda x : round(x.total_seconds() / 60.0, 2))
df1['od_total_time'].head()
```

Out[31]:
```
0    1260.60
1     999.51
2      58.83
3     122.78
4     834.64
Name: od_total_time, dtype: float64
```

In [32]:
```
df2 = df1.groupby(by = 'trip_uuid', as_index = False).agg({'source_center' : 'first',
                                                           'destination_center' : 'last',
                                                           'data' : 'first',
                                                           'route_type' : 'first',
                                                           'trip_creation_time' : 'first',
                                                           'source_name' : 'first',
                                                           'destination_name' : 'last',
                                                           'od_total_time' : 'sum',
                                                           'start_scan_to_end_scan' : 'sum',
                                                           'actual_distance_to_destination' : 'sum',
                                                           'actual_time' : 'sum',
                                                           'osrm_time' : 'sum',
                                                           'osrm_distance' : 'sum',
                                                           'segment_actual_time' : 'sum',
                                                           'segment_osrm_time' : 'sum',
                                                           'segment_osrm_distance' : 'sum'})
df2
```

Out[32]:

	trip_uuid	source_center	destination_center	data	route_type	trip_creation_time	source_name	destination_nai
0	trip-153671041653548748	IND209304AAA	IND209304AAA	training	FTL	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	Kanpur_Central_H (Uttar Prade:
1	trip-153671042288605164	IND561203AAB	IND561203AAB	training	Carting	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	Doddablpur_ChikaDPP (Karnatal
2	trip-153671043369099517	IND000000ACB	IND000000ACB	training	FTL	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)	Gurgaon_Bilaspur_ (Haryaı
3	trip-153671046011330457	IND400072AAB	IND401104AAA	training	Carting	2018-09-12 00:01:00.113710	Mumbai Hub (Maharashtra)	Mumbai_MiraRd_ (Maharasht
4	trip-153671052974046625	IND583101AAA	IND583119AAA	training	FTL	2018-09-12 00:02:09.740725	Bellary_Dc (Karnataka)	Sandur_WrdN1DPP (Karnatal
...	...	...	...	...	...	...	...	...
14812	trip-153861095625827784	IND160002AAC	IND160002AAC	test	Carting	2018-10-03 23:55:56.258533	Chandigarh_Mehmdpur_H (Punjab)	Chandigarh_Mehmdpur (Punj;
14813	trip-153861104386292051	IND121004AAB	IND121004AAA	test	Carting	2018-10-03 23:57:23.863155	FBD_Balabhgarh_DPC (Haryana)	Faridabad_Blbgarh_I (Haryaı
14814	trip-153861106442901555	IND208006AAA	IND208006AAA	test	Carting	2018-10-03 23:57:44.429324	Kanpur_GovndNgr_DC (Uttar Pradesh)	Kanpur_GovndNgr_I (Uttar Prade:
14815	trip-153861115439069069	IND627005AAA	IND628204AAA	test	Carting	2018-10-03 23:59:14.390954	Tirunelveli_VdkkuSrt_I (Tamil Nadu)	Tirchchndr_Shnmgprm (Tamil Na(
14816	trip-153861118270144424	IND583119AAA	IND583119AAA	test	FTL	2018-10-03 23:59:42.701692	Sandur_WrdN1DPP_D (Karnataka)	Sandur_WrdN1DPP (Karnatal

14817 rows × 17 columns

In [33]:
```
def location_name_to_state(x):
    l = x.split('(')
    if len(l) == 1:
        return l[0]
    else:
        return l[1].replace(')', "")
```

In [34]:
```
def location_name_to_city(x):
    if 'location' in x:
        return 'unknown_city'
    else:
        l = x.split()[0].split('_')
        if 'CCU' in x:
            return 'Kolkata'
        elif 'MAA' in x.upper():
            return 'Chennai'
        elif ('HBR' in x.upper()) or ('BLR' in x.upper()):
            return 'Bengaluru'
        elif 'FBD' in x.upper():
            return 'Faridabad'
        elif 'BOM' in x.upper():
            return 'Mumbai'
        elif 'DEL' in x.upper():
            return 'Delhi'
        elif 'OK' in x.upper():
            return 'Delhi'
        elif 'GZB' in x.upper():
            return 'Ghaziabad'
        elif 'GGN' in x.upper():
            return 'Gurgaon'
        elif 'AMD' in x.upper():
            return 'Ahmedabad'
        elif 'CJB' in x.upper():
            return 'Coimbatore'
        elif 'HYD' in x.upper():
            return 'Hyderabad'
        return l[0]
```

In [35]:
```
def location_name_to_place(x):
    # We will remove state
    x = x.split(' (')[0]
    len_ = len(x.split('_'))
    if len_ >= 3:
        return x.split('_')[1]
    # Small cities have same city and place name
    if len_ == 2:
        return x.split('_')[0]
    # Now we need to deal with edge cases or imporper name convention
    #if len(x.split(' ')) == 2:
    return x.split(' ')[0]
```

In [36]:
```
def location_name_to_code(x):
    # We will remove state
    x = x.split(' (')[0]
    if len(x.split('_')) >= 3 :
        return x.split('_')[-1]
    return 'none'
```

In [37]:
```
df2['source_state'] = df2['source_name'].apply(location_name_to_state)
print('Number of unique source states :', df2['source_state'].nunique())
print()
print('Name of unique source states :', df2['source_state'].unique())
```

```
Number of unique source states : 34

Name of unique source states : ['Uttar Pradesh' 'Karnataka' 'Haryana' 'Maharashtra' 'Tamil Nadu'
 'Gujarat' 'Delhi' 'Telangana' 'Rajasthan' 'Assam' 'Madhya Pradesh'
 'West Bengal' 'Andhra Pradesh' 'Punjab' 'Chandigarh' 'Goa' 'Jharkhand'
 'Pondicherry' 'Orissa' 'Uttarakhand' 'Himachal Pradesh' 'Kerala'
 'Arunachal Pradesh' 'Bihar' 'Chhattisgarh' 'Dadra and Nagar Haveli'
 'Jammu & Kashmir' 'Mizoram' 'Nagaland' 'location_9' 'location_3'
 'location_2' 'location_14' 'location_7']
```

In [38]:
```
df2['source_city'] = df2['source_name'].apply(location_name_to_city)
print('Number of unique source cities :', df2['source_city'].nunique())
print()
print('Name of unique source cities (Displaying first 100 names):', df2['source_city'].unique()[:100])
```

```
Number of unique source cities : 690

Name of unique source cities (Displaying first 100 names): ['Kanpur' 'Doddablpur' 'Gurgaon' 'Mumbai' 'Bellary' 'Chenna
i' 'Bengaluru'
 'Surat' 'Delhi' 'Pune' 'Faridabad' 'Shirala' 'Hyderabad' 'Thirumalagiri'
 'Gulbarga' 'Jaipur' 'Allahabad' 'Guwahati' 'Narsinghpur' 'Shrirampur'
 'Madakasira' 'Sonari' 'Dindigul' 'Jalandhar' 'Chandigarh' 'Deoli'
 'Pandharpur' 'Kolkata' 'Bhandara' 'Kurnool' 'Bhiwandi' 'Bhatinda'
 'RoopNagar' 'Bantwal' 'Lalru' 'Kadi' 'Shahdol' 'Gangakher' 'Durgapur'
 'Vapi' 'Jamjodhpur' 'Jetpur' 'Mehsana' 'Jabalpur' 'Junagadh' 'Gundlupet'
 'Mysore' 'Goa' 'Bhopal' 'Sonipat' 'Himmatnagar' 'Jamshedpur'
 'Pondicherry' 'Anand' 'Udgir' 'Nadiad' 'Villupuram' 'Purulia'
 'Bhubaneshwar' 'Bamangola' 'Tiruppattur' 'Kotdwara' 'Medak' 'Bangalore'
 'Dhrangadhra' 'Hospet' 'Ghumarwin' 'Agra' 'Sitapur' 'Canacona' 'Bilimora'
 'SultnBthry' 'Lucknow' 'Vellore' 'Bhuj' 'Dinhata' 'Margherita' 'Boisar'
 'Vizag' 'Tezpur' 'Koduru' 'Tirupati' 'Pen' 'Ahmedabad' 'Faizabad'
 'Gandhinagar' 'Anantapur' 'Betul' 'Panskura' 'Rasipurm' 'Sankari'
 'Jorhat' 'PNQ' 'Srikakulam' 'Dehradun' 'Jassur' 'Sawantwadi' 'Shajapur'
 'Ludhiana' 'GreaterThane']
```

In [39]:
```
df2['source_place'] = df2['source_name'].apply(location_name_to_place)
print('Number of unique source places :', df2['source_place'].nunique())
print()
print('Name of unique source places (Displaying first 100 names):', df2['source_place'].unique()[:100])
```

```
Number of unique source places : 774

Name of unique source places (Displaying first 100 names): ['Central' 'ChikaDPP' 'Bilaspur' 'Mumbai' 'Bellary' 'Chenna
i' 'Chrompet'
 'HBR' 'Lajpat' 'North' 'Balabhgarh' 'Shamshbd' 'Xroad' 'Nehrugnj'
 'Nangli' 'Guwahati' 'KndliDPP' 'DavkharRd' 'Bandel' 'RTCStand' 'KGAirprt'
 'Jalandhar' 'Mthurard' 'Mullanpr' 'RajCmplx' 'Beliaghata' 'RjnaiDPP'
 'AbbasNgr' 'Mankoli' 'Bhatinda' 'Airport' 'Jaipur' 'Gateway' 'Tathawde'
 'ChotiHvl' 'Trmltmpl' 'OnkarDPP' 'Mehmdpur' 'KaranNGR' 'Sohagpur'
 'Busstand' 'IndEstat' 'Court' 'Jetpur' 'Panchot' 'Adhartal' 'DumDum'
 'Bomsndra' 'Junagadh' 'Swamylyt' 'Yadvgiri' 'Goa' 'Bhopal' 'Kundli'
 'Himmatnagar' 'Vasanthm' 'Poonamallee' 'VUNagar' 'NlgaonRd' 'Nadiad'
 'Bnnrghta' 'Thirumtr' 'GariDPP' 'Bhubaneshwar' 'Jogshwri' 'KoilStrt'
 'CotnGren' 'Nzbadrd' 'Dwaraka' 'Nelmngla' 'NvygRDPP' 'Hospet' 'Gndhichk'
 'Chowk' 'CharRsta' 'Bilimora' 'Kollgpra' 'Lucknow' 'Peenya' 'GndhiNgr'
 'Sanpada' 'Bhuj' 'WrdN4DPP' 'Sakinaka' 'CivilHPL' 'OstwlEmp' 'Vizag'
 'Mhbhirab' 'MGRoad' 'Balajicly' 'BljiMrkt' 'Dankuni' 'Trnsport' 'AMD'
 'East' 'Mithakal' 'TrnspNgr' 'Gandhinagar' 'KamaStrt' 'PatelWrd']
```

In [40]:
```
df2['source_code'] = df2['source_name'].apply(location_name_to_code)
print('Number of unique source state codes :', df2['source_code'].nunique())
print()
print('Name of unique source state codes :', df2['source_code'].unique())
```

```
Number of unique source state codes : 33

Name of unique source state codes : ['6' 'D' 'HB' 'none' 'DPC' '12' 'IP' '3' 'H' 'I' '7' '1' '9' '2' 'L' 'DC'
 'M' 'RP' '21' '4' 'Pc' 'PC' 'C' 'V' 'CP' '8' 'Dc' 'P' '11' '5' '20' '15'
 '10']
```

In [41]:
```
df2[['source_state', 'source_city', 'source_place', 'source_code']]
```

Out[41]:

	source_state	source_city	source_place	source_code
0	Uttar Pradesh	Kanpur	Central	6
1	Karnataka	Doddablpur	ChikaDPP	D
2	Haryana	Gurgaon	Bilaspur	HB
3	Maharashtra	Mumbai	Mumbai	none
4	Karnataka	Bellary	Bellary	none
...	...	...	...	...
14812	Punjab	Chandigarh	Mehmdpur	H
14813	Haryana	Faridabad	Balabhgarh	DPC
14814	Uttar Pradesh	Kanpur	GovndNgr	DC
14815	Tamil Nadu	Tirunelveli	VdkkuSrt	I
14816	Karnataka	Sandur	WrdN1DPP	D

14817 rows × 4 columns

2B. Destination Name: Split and extract features out of destination. City-place-code (State):

In [42]:
```
df2['destination_state'] = df2['destination_name'].apply(location_name_to_state)
print('Unique number of destination states :', df2['destination_state'].nunique())
print()
print('Name of unique destination states :', df2['destination_state'].unique())
```

```
Unique number of destination states : 39

Name of unique destination states : ['Uttar Pradesh' 'Karnataka' 'Haryana' 'Maharashtra' 'Tamil Nadu'
 'Gujarat' 'Delhi' 'Telangana' 'Rajasthan' 'Madhya Pradesh' 'Assam'
 'West Bengal' 'Andhra Pradesh' 'Punjab' 'Chandigarh'
 'Dadra and Nagar Haveli' 'Orissa' 'Bihar' 'Jharkhand' 'Goa' 'Uttarakhand'
 'Himachal Pradesh' 'Kerala' 'Arunachal Pradesh' 'Mizoram' 'Chhattisgarh'
 'Jammu & Kashmir' 'Nagaland' 'Meghalaya' 'Tripura' 'location_13'
 'location_6' 'location_2' 'location_7' 'location_3' 'location_5'
 'location_12' 'location_11' 'Daman & Diu']
```

In [43]:
```
df2['destination_city'] = df2['destination_name'].apply(location_name_to_city)
print('Unique number of destination cities :', df2['destination_city'].nunique())
print()
print('Name of unique destination cities (Displaying first 100 names):',df2['destination_city'].unique()[:100])
```

```
Unique number of destination cities : 806

Name of unique destination cities (Displaying first 100 names): ['Kanpur' 'Doddablpur' 'Gurgaon' 'Mumbai' 'Sandur' 'Ch
ennai' 'Bengaluru'
 'Surat' 'Delhi' 'PNQ' 'Faridabad' 'Ratnagiri' 'Bangalore' 'Hyderabad'
 'Aland' 'Jaipur' 'Satna' 'Guwahati' 'Bareli' 'Nashik' 'Hooghly'
 'Sivasagar' 'Palani' 'Jalandhar' 'Chandigarh' 'Yavatmal' 'Sangola'
 'Kolkata' 'Savner' 'Kurnool' 'Bhatinda' 'Bhiwandi' 'Barnala' 'Murbad'
 'Kadaba' 'Gulbarga' 'Naraingarh' 'Ludhiana' 'Kadi' 'Jabalpur' 'Gangakher'
 'Bankura' 'Silvassa' 'Porbandar' 'Jetpur' 'Khammam' 'Mehsana' 'Katni'
 'Una' 'Malavalli' 'HDKote' 'Radhanpur' 'Visakhapatnam' 'Pune' 'Bhopal'
 'Bhubaneshwar' 'Allahabad' 'Sonipat' 'Himmatnagar' 'Sasaram' 'Ranchi'
 'Thiruvarur' 'Ghaziabad' 'Anand' 'Nanded' 'Noida' 'Nadiad' 'Virudhchlm'
 'Durgapur' 'Bhadrak' 'Goa' 'Balurghat' 'Hisar' 'Tiruppattur' 'Kotdwara'
 'Yellareddy' 'Halvad' 'Hospet' 'JognderNgr' 'Kirauli' 'Dhaurahara'
 'Canacona' 'Vansda' 'Mananthavady' 'Lucknow' 'Silchar' 'Bhuj' 'Pundibari'
 'LowerParel' 'Changlang' 'Boisar' 'Tezpur' 'Koduru' 'Gudur' 'Pen'
 'Ahmedabad' 'Akbarpur' 'Purnia' 'Aurangabad' 'Anantapur']
```

In [44]:
```
df2['destination_place'] = df2['destination_name'].apply(location_name_to_place)
print('Unique number of destination places :', df2['destination_place'].nunique())
print()
print('Name of unique destination places (Displaying first 100 names):',df2['destination_place'].unique()[:100])
```

```
Unique number of destination places : 876

Name of unique destination places (Displaying first 100 names): ['Central' 'ChikaDPP' 'Bilaspur' 'MiraRd' 'WrdN1DPP'
 'Chennai' 'Vandalur'
 'HBR' 'Delhi' 'PNQ' 'Faridabad' 'MjgaonRd' 'Nelmngla' 'Uppal' 'RazaviRd'
 'Janakpuri' 'Guwahati' 'SourvDPP' 'Varachha' 'TgrniaRD' 'Hooghly'
 'Gokulam' 'Babupaty' 'Bomsndra' 'Alwal' 'RjndraRd' 'Jalandhar' 'Mehmdpur'
 'Sanpada' 'JajuDPP' 'Dankuni' 'Wagodha' 'AbbasNgr' 'Balabhgarh'
 'Bhatinda' 'Mankoli' 'Shamshbd' 'Barnala' 'SnkunDPP' 'Kharar' 'AnugrDPP'
 'Nehrugnj' 'Ward2DPP' 'MilrGanj' 'KaranNGR' 'Adhartal' 'Poonamallee'
 'Busstand' 'BhowmDPP' 'Samrvrni' 'Porbandar' 'Jetpur' 'NSTRoad' 'Panchot'
 'Bargawan' 'KGAirprt' 'Mamlatdr' 'SulthnRd' 'Jogeshwri' 'BegurRD'
 'Santalpr' 'Gajuwaka' 'Tathawde' 'Trnsport' 'Bhubaneshwar' 'Jaipur'
 'Kundli' 'Himmatnagar' 'Ranchi' 'Rohini' 'Bypasrd' 'Mohan' 'Madhavaram'
 'Vaghasi' 'Aswningr' 'Sec 02' 'Nadiad' 'SelamRd' 'Bhopal' 'Goa' 'Porur'
 'Perungudi' 'AkhirDPP' 'IndstlAr' 'Raiprvlg' 'Jhilmil' 'KoilStrt'
 'Nzbadrd' 'Mumbai' 'JKRoad' 'Mayapuri' 'Hoodi' 'CrossRD' 'Hospet' 'Dhelu'
 'AchneraRD' 'JPNagar' 'KHRoad' 'TahsilRD' 'Kishangarh']
```

In [45]:
```
df2['destination_code'] = df2['destination_name'].apply(location_name_to_code)
print('Unique number of destination codes :', df2['destination_code'].nunique())
print()
print('Name of unique destination codes (Displaying first 100 names):',df2['destination_code'].unique()[:100])
```

```
Unique number of destination codes : 34

Name of unique destination codes (Displaying first 100 names): ['6' 'D' 'HB' 'IP' 'none' 'Dc' '3' 'H' 'I' '7' '2' 'DC'
 'DPC' 'L' '1' 'PC'
 'Pc' '12' '9' '10' 'RPC' 'P' 'GW' 'Gateway' '8' '21' '4' 'INT' 'M' '5'
 'C' '23' '20' 'CP']
```

In [46]:
```
df2[['destination_state', 'destination_city', 'destination_place', 'destination_code']]
```

Out[46]:

	destination_state	destination_city	destination_place	destination_code
0	Uttar Pradesh	Kanpur	Central	6
1	Karnataka	Doddablpur	ChikaDPP	D
2	Haryana	Gurgaon	Bilaspur	HB
3	Maharashtra	Mumbai	MiraRd	IP
4	Karnataka	Sandur	WrdN1DPP	D
...	...	...	...	...
14812	Punjab	Chandigarh	Mehmdpur	H
14813	Haryana	Faridabad	Blbgarh	DC
14814	Uttar Pradesh	Kanpur	GovndNgr	DC
14815	Tamil Nadu	Tirchchndr	Shnmgprm	D
14816	Karnataka	Sandur	WrdN1DPP	D

14817 rows × 4 columns

2C. Trip_creation_time: Extract features like month, year and day etc:

In [47]:
```
df2['trip_creation_date'] = pd.to_datetime(df2['trip_creation_time'].dt.date)

df2['trip_creation_year'] = df2['trip_creation_time'].dt.year
df2['trip_creation_month'] = df2['trip_creation_time'].dt.month
df2['trip_creation_day'] = df2['trip_creation_time'].dt.day
df2['trip_creation_week'] = df2['trip_creation_time'].dt.isocalendar().week
df2['trip_creation_hour'] = df2['trip_creation_time'].dt.hour
df2['trip_day_of_week'] = df2['trip_creation_time'].dt.dayofweek
```

In [48]:
```
df2[['trip_creation_year', 'trip_creation_month', 'trip_creation_day', 'trip_creation_week', 'trip_creation_hour', 'trip
```

Out[48]:

	trip_creation_year	trip_creation_month	trip_creation_day	trip_creation_week	trip_creation_hour	trip_day_of_week
0	2018	9	12	37	0	2
1	2018	9	12	37	0	2
2	2018	9	12	37	0	2
3	2018	9	12	37	0	2
4	2018	9	12	37	0	2
...	...	...	...	...	...	...
14812	2018	10	3	40	23	2
14813	2018	10	3	40	23	2
14814	2018	10	3	40	23	2
14815	2018	10	3	40	23	2
14816	2018	10	3	40	23	2

14817 rows × 6 columns

Finding the structure of data after extracting features and data cleaning:

In [49]:
```
df2.shape
```

Out[49]: (14817, 32)

In [50]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14817 entries, 0 to 14816
Data columns (total 32 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   trip_uuid                       14817 non-null  object
 1   source_center                   14817 non-null  object
 2   destination_center              14817 non-null  object
 3   data                            14817 non-null  category
 4   route_type                      14817 non-null  category
 5   trip_creation_time              14817 non-null  datetime64[ns]
 6   source_name                     14817 non-null  object
 7   destination_name                14817 non-null  object
 8   od_total_time                   14817 non-null  float64
 9   start_scan_to_end_scan          14817 non-null  float64
 10  actual_distance_to_destination  14817 non-null  float64
 11  actual_time                     14817 non-null  float64
 12  osrm_time                       14817 non-null  float64
 13  osrm_distance                   14817 non-null  float64
 14  segment_actual_time             14817 non-null  float64
 15  segment_osrm_time               14817 non-null  float64
 16  segment_osrm_distance           14817 non-null  float64
 17  source_state                    14817 non-null  object
 18  source_city                     14817 non-null  object
 19  source_place                    14817 non-null  object
 20  source_code                     14817 non-null  object
 21  destination_state               14817 non-null  object
 22  destination_city                14817 non-null  object
 23  destination_place               14817 non-null  object
 24  destination_code                14817 non-null  object
 25  trip_creation_date              14817 non-null  datetime64[ns]
 26  trip_creation_year              14817 non-null  int64
 27  trip_creation_month             14817 non-null  int64
 28  trip_creation_day               14817 non-null  int64
 29  trip_creation_week              14817 non-null  UInt32
 30  trip_creation_hour              14817 non-null  int64
 31  trip_day_of_week                14817 non-null  int64
dtypes: UInt32(1), category(2), datetime64[ns](2), float64(9), int64(5), object(13)
memory usage: 3.4+ MB
```

In [51]:
```
df2.describe().T
```

Out[51]:

	count	mean	std	min	25%	50%	75%	max
od_total_time	14817.0	531.69763	658.868223	23.46	149.93	280.77	638.2	7898.55
start_scan_to_end_scan	14817.0	530.810016	658.705957	23.0	149.0	280.0	637.0	7898.0
actual_distance_to_destination	14817.0	164.477838	305.388147	9.002461	22.837239	48.474072	164.583208	2186.531787
actual_time	14817.0	357.143754	561.396157	9.0	67.0	149.0	370.0	6265.0
osrm_time	14817.0	161.384018	271.360995	6.0	29.0	60.0	168.0	2032.0
osrm_distance	14817.0	204.344689	370.395573	9.0729	30.8192	65.6188	208.475	2840.081
segment_actual_time	14817.0	353.892286	556.247965	9.0	66.0	147.0	367.0	6230.0
segment_osrm_time	14817.0	180.949787	314.542047	6.0	31.0	65.0	185.0	2564.0
segment_osrm_distance	14817.0	223.201161	416.628374	9.0729	32.6545	70.1544	218.8024	3523.6324
trip_creation_year	14817.0	2018.0	0.0	2018.0	2018.0	2018.0	2018.0	2018.0
trip_creation_month	14817.0	9.120672	0.325757	9.0	9.0	9.0	9.0	10.0
trip_creation_day	14817.0	18.37079	7.893275	1.0	14.0	19.0	25.0	30.0
trip_creation_week	14817.0	38.295944	0.967872	37.0	38.0	38.0	39.0	40.0
trip_creation_hour	14817.0	12.449821	7.986553	0.0	4.0	14.0	20.0	23.0
trip_day_of_week	14817.0	2.919349	1.927769	0.0	1.0	3.0	5.0	6.0

In [52]:
```
df2.describe(include = object).T
```

Out[52]:

	count	unique	top	freq
trip_uuid	14817	14817	trip-153671041653548748	1
source_center	14817	938	IND000000ACB	1063
destination_center	14817	1042	IND000000ACB	821
source_name	14817	938	Gurgaon_Bilaspur_HB (Haryana)	1063
destination_name	14817	1042	Gurgaon_Bilaspur_HB (Haryana)	821
source_state	14817	34	Maharashtra	2714
source_city	14817	690	Mumbai	1442
source_place	14817	774	Bilaspur	1085
source_code	14817	33	HB	3222
destination_state	14817	39	Maharashtra	2561
destination_city	14817	806	Mumbai	1548
destination_place	14817	876	Bilaspur	864
destination_code	14817	34	D	2868

Data Analysis for Vital Information:

1. I am intrested to know how many trips are created on the hourly basis:

In [53]:
```
df2['trip_creation_hour'].unique()
```

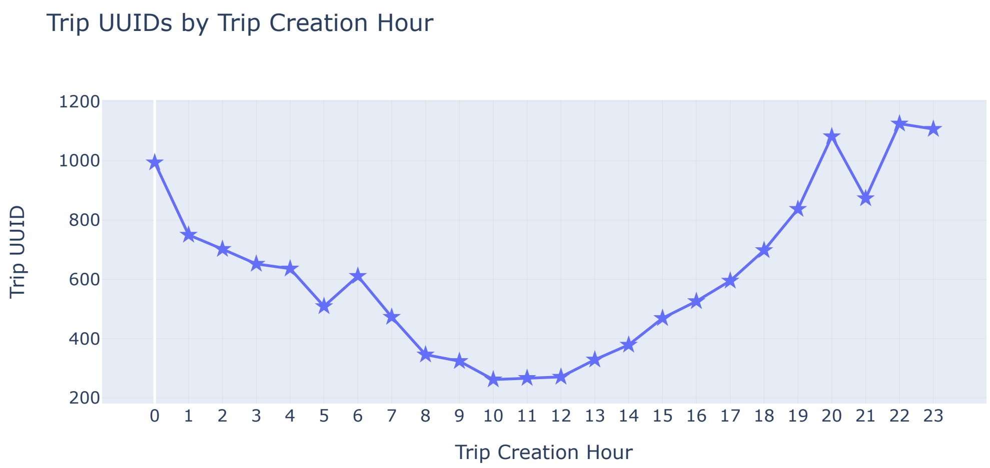
Out[53]:
```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
       17, 18, 19, 20, 21, 22, 23], dtype=int64)
```

In [54]:
```
df_hour = df2.groupby(by = 'trip_creation_hour')['trip_uuid'].count().to_frame().reset_index()
df_hour.head()
```

Out[54]:

	trip_creation_hour	trip_uuid
0	0	994
1	1	750
2	2	702
3	3	652
4	4	636

In [55]:
```
# Create the line plot with markers using Plotly
fig = go.Figure()
# Adding the line plot
fig.add_trace(go.Scatter(x = df_hour['trip_creation_hour'],
                         y = df_hour['trip_uuid'],
                         mode = 'lines+markers',
                         marker = dict(symbol = 'star',
                                       size = 10),    # Adds markers with star symbol
                         line = dict(width = 2)))
# Customize the layout
fig.update_layout(title = "Trip UUIDs by Trip Creation Hour",
                  xaxis_title = "Trip Creation Hour",
                  yaxis_title = "Trip UUID",
                  xaxis = dict(tickmode = 'array',
                               tickvals = list(range(0, 24))),  # Set x-ticks from 0 to 23
                  width = 800,
                  height = 400     # Set figure size
                 )
# Add gridlines with custom color and style
fig.update_xaxes(showgrid = True, gridcolor = 'LightGray')
fig.update_yaxes(showgrid = True, gridcolor = 'LightGray')
# Show the figure
fig.show()
```



Insights:

- **It can be inferred from the above plot that the number of trips start increasing after the noon, becomes maximum at 10 P.M and then start decreasing.**

---

2. I am intrested to know how many trips are created for different days of the month:

In [56]:
```
df2['trip_creation_day'].unique()
```

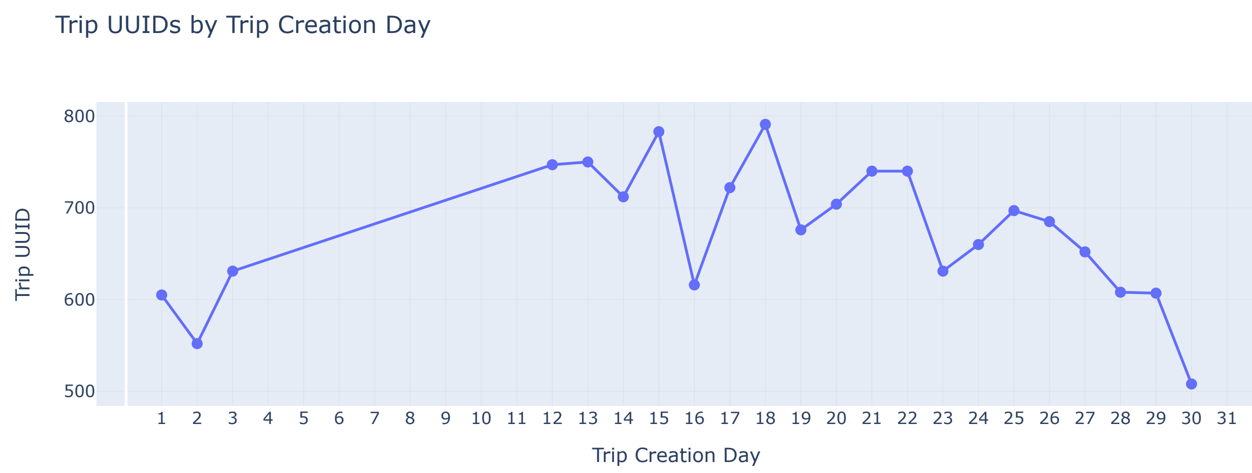
Out[56]:
```
array([12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28,
       29, 30,  1,  2,  3], dtype=int64)
```

In [57]:
```
df_day = df2.groupby(by = 'trip_creation_day')['trip_uuid'].count().to_frame().reset_index()
df_day.head()
```

Out[57]:

	trip_creation_day	trip_uuid
0	1	605
1	2	552
2	3	631
3	12	747
4	13	750

In [58]:
```
# Create the line plot with markers using Plotly
fig = go.Figure()
# Adding the line plot
fig.add_trace(go.Scatter(x = df_day['trip_creation_day'],
                         y = df_day['trip_uuid'],
                         mode = 'lines+markers',
                         marker = dict(symbol = 'circle',
                                       size = 8),  # Adds circle markers
                         line = dict(width = 2)
                        )
             )
# Customize the layout
fig.update_layout(title = "Trip UUIDs by Trip Creation Day",
                  xaxis_title = "Trip Creation Day",
                  yaxis_title = "Trip UUID",
                  xaxis = dict(tickmode = 'array',
                               tickvals = list(range(1, 32))),  # Set x-ticks from 1 to 31
                  width = 1000,
                  height = 400     # Set figure size
                 )
# Add gridlines with custom color and style
fig.update_xaxes(showgrid = True, gridcolor = 'LightGray')
fig.update_yaxes(showgrid = True, gridcolor = 'LightGray')
# Show the figure
fig.show()
```



Insights:

- **It can be inferred from the above plot that most of the trips are created in the mid of the month.**
- **That means customers usually make more orders in the mid of the month.**

---

3. I am intrested to know how many trips are created for different weeks:

In [59]:
```
df2['trip_creation_week'].unique()
```

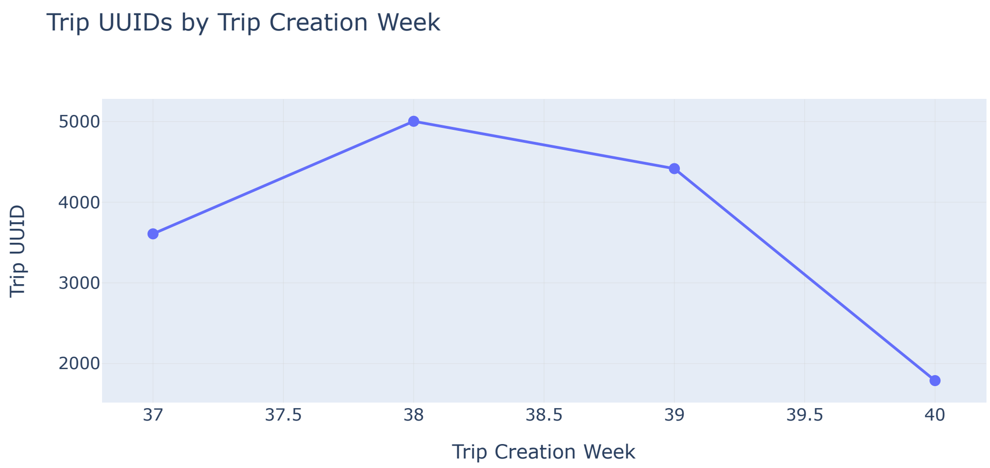
Out[59]:
```
<IntegerArray>
[37, 38, 39, 40]
Length: 4, dtype: UInt32
```

In [60]:
```
df_week = df2.groupby(by = 'trip_creation_week')['trip_uuid'].count().to_frame().reset_index()
df_week.head()
```

Out[60]:

	trip_creation_week	trip_uuid
0	37	3608
1	38	5004
2	39	4417
3	40	1788

In [61]:
```
# Create the line plot with markers using Plotly
fig = go.Figure()
# Adding the line plot
fig.add_trace(go.Scatter(x = df_week['trip_creation_week'],
                         y = df_week['trip_uuid'],
                         mode = 'lines+markers',
                         marker = dict(symbol = 'circle',
                                       size = 8),  # Adds circle markers
                         line = dict(width = 2)
                        )
             )
# Customize the layout
fig.update_layout(title = "Trip UUIDs by Trip Creation Week",
                  xaxis_title = "Trip Creation Week",
                  yaxis_title = "Trip UUID",
                  width = 800,
                  height = 400    # Set figure size
                 )
# Add gridlines with custom color and style
fig.update_xaxes(showgrid = True, gridcolor = 'LightGray')
fig.update_yaxes(showgrid = True, gridcolor = 'LightGray')
# Show the figure
fig.show()
```



Insights:

- **It can be inferred from the above plot that most of the trips are created in the 38th week.**

---

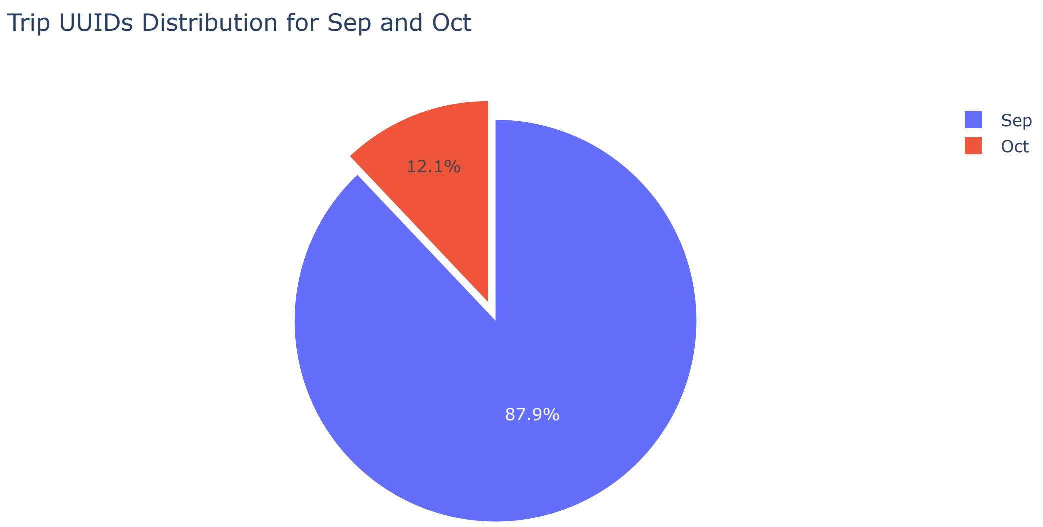
4. I am intrested to know how many trips are created in the given two months:

In [62]:
```
df_month = df2.groupby(by = 'trip_creation_month')['trip_uuid'].count().to_frame().reset_index()
df_month['perc'] = np.round(df_month['trip_uuid'] * 100/ df_month['trip_uuid'].sum(), 2)
df_month.head()
```

Out[62]:

	trip_creation_month	trip_uuid	perc
0	9	13029	87.93
1	10	1788	12.07

In [63]:
```
# Create the pie chart using Plotly
fig = go.Figure()
# Adding the pie chart
fig.add_trace(go.Pie(
    labels = ['Sep', 'Oct'],              # Labels for the pie chart
    values = df_month['trip_uuid'],       # Values for the pie chart
    pull = [0, 0.1],                      # Exploding the second slice (Oct)
    hoverinfo = 'label+percent',          # Show label and percentage on hover
    textinfo = 'percent',                 # Show percentage inside the slices
))
# Customize the layout
fig.update_layout(title = "Trip UUIDs Distribution for Sep and Oct",
                  width = 800,
                  height = 500            # Set figure size
                 )
# Show the figure
fig.show()
```



---

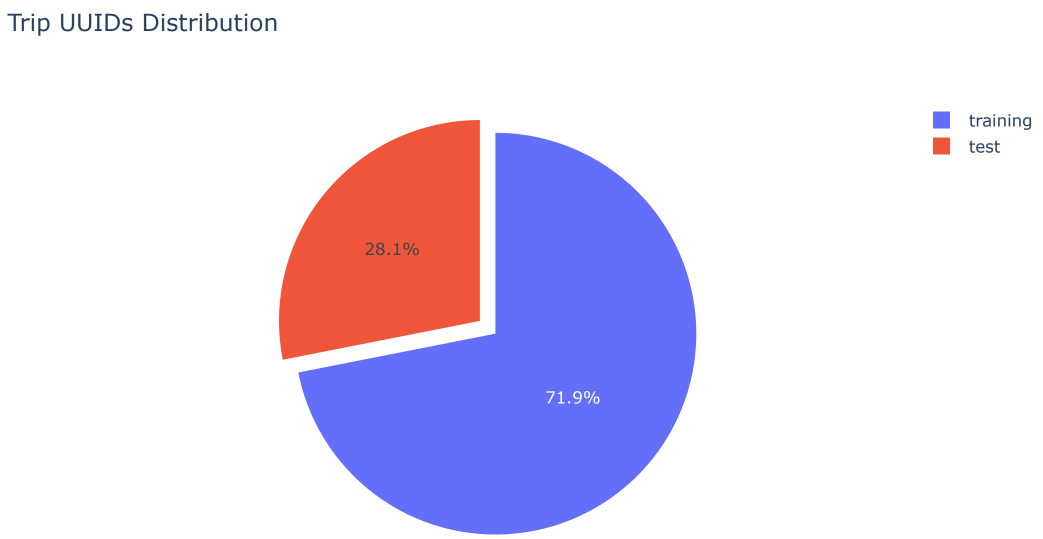
5. I am interested to know the distribution of trip data for the orders:

In [64]:
```
df_data = df2.groupby(by = 'data')['trip_uuid'].count().to_frame().reset_index()
df_data['perc'] = np.round(df_data['trip_uuid'] * 100/ df_data['trip_uuid'].sum(), 2)
df_data.head()
```

Out[64]:

	data	trip_uuid	perc
0	test	4163	28.1
1	training	10654	71.9

In [65]:
```
# Create the pie chart using Plotly
fig = go.Figure()
# Adding the pie chart
fig.add_trace(go.Pie(
    labels = df_data['data'],            # Labels for the pie chart
    values = df_data['trip_uuid'],       # Values for the pie chart
    pull = [0, 0.1],                     # Exploding the second slice
    hoverinfo = 'label+percent',         # Show label and percentage on hover
    textinfo = 'percent',                # Show percentage inside the slices
))
# Customize the layout
fig.update_layout(title = "Trip UUIDs Distribution",
                  width = 800,
                  height = 500           # Set figure size
                 )
# Show the figure
fig.show()
```



---

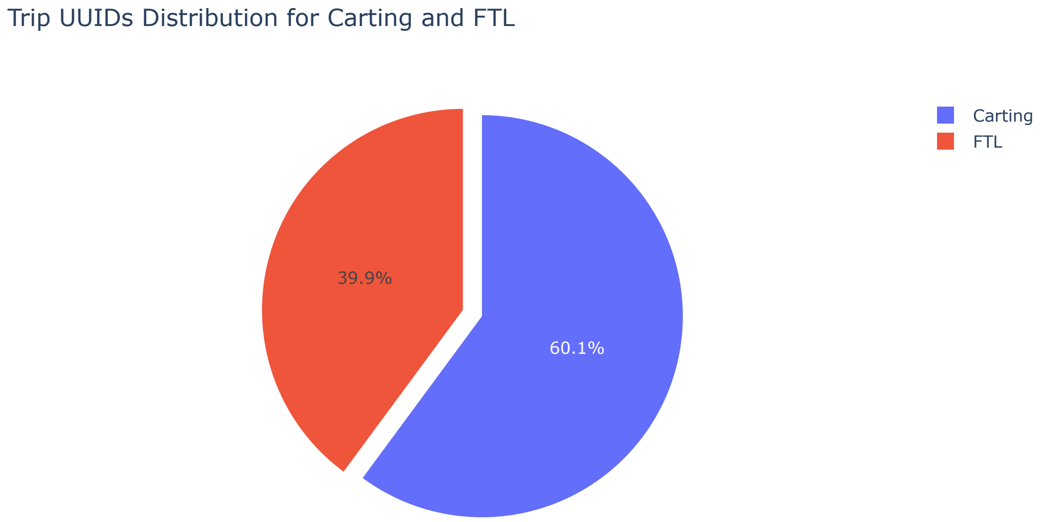
6. I am interested to know the distribution of route types for the orders:

In [66]:
```
df_route = df2.groupby(by = 'route_type')['trip_uuid'].count().to_frame().reset_index()
df_route['perc'] = np.round(df_route['trip_uuid'] * 100/ df_route['trip_uuid'].sum(), 2)
df_route.head()
```

Out[66]:

	route_type	trip_uuid	perc
0	Carting	8908	60.12
1	FTL	5909	39.88

In [67]:
```
# Create the pie chart using Plotly
fig = go.Figure()
# Adding the pie chart
fig.add_trace(go.Pie(
    labels = ['Carting', 'FTL'],          # Labels for the pie chart
    values = df_route['trip_uuid'],       # Values for the pie chart
    pull = [0, 0.1],                      # Exploding the second slice (FTL)
    hoverinfo = 'label+percent',          # Show label and percentage on hover
    textinfo = 'percent',                 # Show percentage inside the slices
))
# Customize the layout
fig.update_layout(title = "Trip UUIDs Distribution for Carting and FTL",
                  width = 800,
                  height = 500            # Set figure size
                 )
# Show the figure
fig.show()
```



7. I am interested to know what is the distribution of number of trips created from different

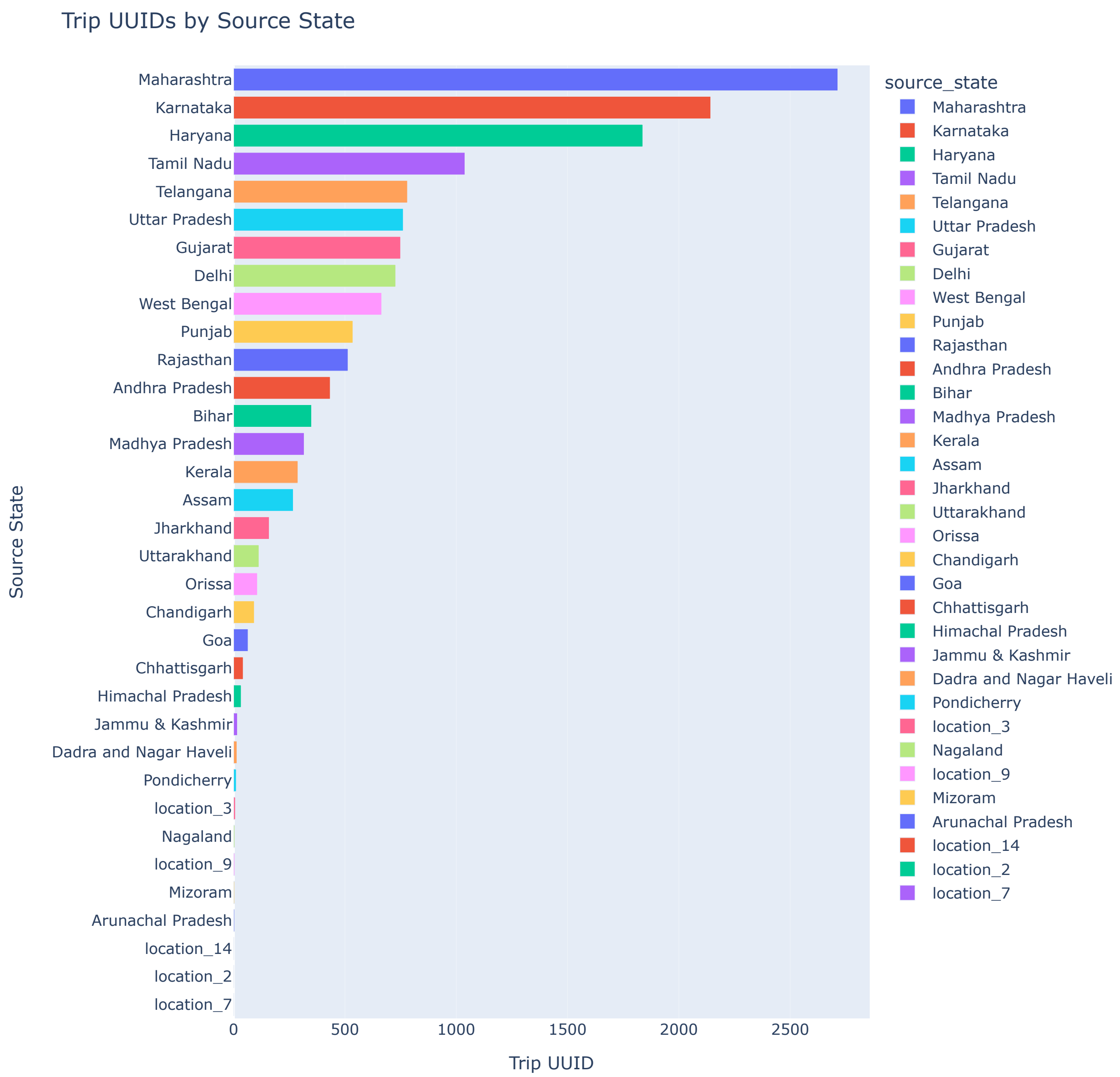
states:

In [68]:
```
df_source_state = df2.groupby(by = 'source_state')['trip_uuid'].count().to_frame().reset_index()
df_source_state['perc'] = np.round(df_source_state['trip_uuid'] * 100/ df_source_state['trip_uuid'].sum(), 2)
df_source_state = df_source_state.sort_values(by = 'trip_uuid', ascending = False)
df_source_state.head()
```

Out[68]:

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

In [69]:
```
# Sort the DataFrame by 'trip_uuid' in descending order
df_sorted = df_source_state.sort_values(by = 'trip_uuid', ascending = False)
# Create the bar chart using Plotly with a multi-color scheme
fig = px.bar(data_frame = df_sorted,
             x = 'trip_uuid',          # X-axis: trip_uuid (the value for the bars)
             y = 'source_state',       # Y-axis: source_state (the categories for the bars)
             color = 'source_state',   # Use source_state to assign different colors to bars
             orientation = 'h',        # Horizontal bar chart
             color_discrete_sequence = px.colors.qualitative.Plotly  # Use a qualitative color palette
)
# Customize the layout
fig.update_layout(title = "Trip UUIDs by Source State",
                  xaxis_title = "Trip UUID",
                  yaxis_title = "Source State",
                  width = 900,
                  height = 900              # Adjust figure size
                 )
# Show the figure
fig.show()
```



Insights:

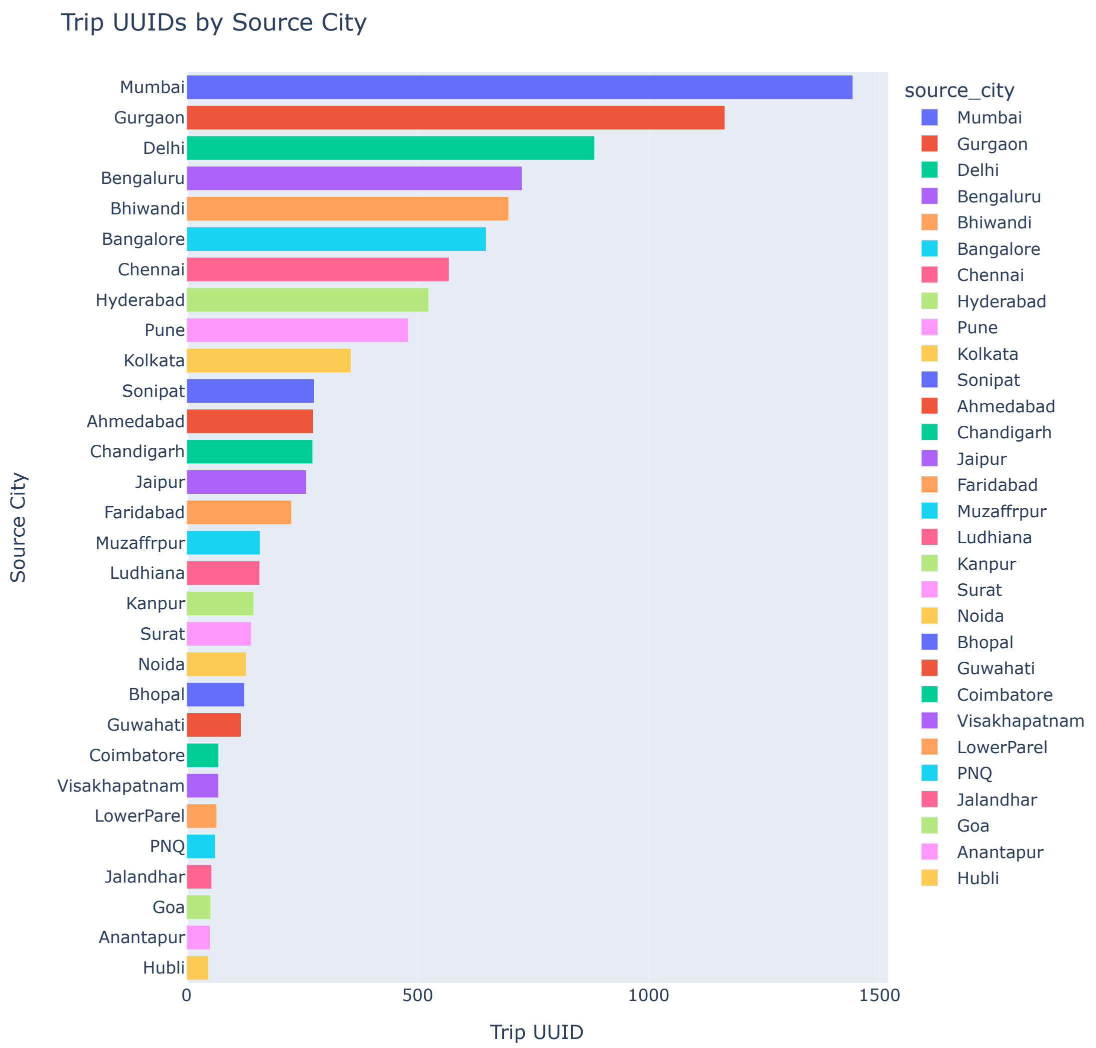
- **It can be seen in the above plot that maximum trips originated from Maharashtra state followed by Karnataka and Haryana.**
- **That means that the seller base is strong in these states.**

In [70]:
```python
df_source_city = df2.groupby(by = 'source_city')['trip_uuid'].count().to_frame().reset_index()
df_source_city['perc'] = np.round(df_source_city['trip_uuid'] * 100/ df_source_city['trip_uuid'].sum(), 2)
df_source_city = df_source_city.sort_values(by = 'trip_uuid', ascending = False)[:30]
df_source_city.head()
```

Out[70]:

	source_city	trip_uuid	perc
439	Mumbai	1442	9.73
237	Gurgaon	1165	7.86
169	Delhi	883	5.96
79	Bengaluru	726	4.90
100	Bhiwandi	697	4.70

In [71]:
```python
# Sort the DataFrame by 'trip_uuid' in descending order
df_sorted_city = df_source_city.sort_values(by = 'trip_uuid', ascending = False)
# Create the bar chart using Plotly with a multi-color scheme
fig = px.bar(data_frame = df_sorted_city,
             x = 'trip_uuid',          # X-axis: trip_uuid (the value for the bars)
             y = 'source_city',        # Y-axis: source_city (the categories for the bars)
             color = 'source_city',    # Use source_city to assign different colors to bars
             orientation = 'h',        # Horizontal bar chart
             color_discrete_sequence = px.colors.qualitative.Plotly  # Use a qualitative color palette
            )
# Customize the layout
fig.update_layout(title = "Trip UUIDs by Source City",
                  xaxis_title = "Trip UUID",
                  yaxis_title = "Source City",
                  width = 800,
                  height = 800   # Adjust figure size to (10, 10)
                 )
# Show the figure
fig.show()
```



Insights:

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

---

9. I am interested to know what is the distribution of number of trips which ended in different

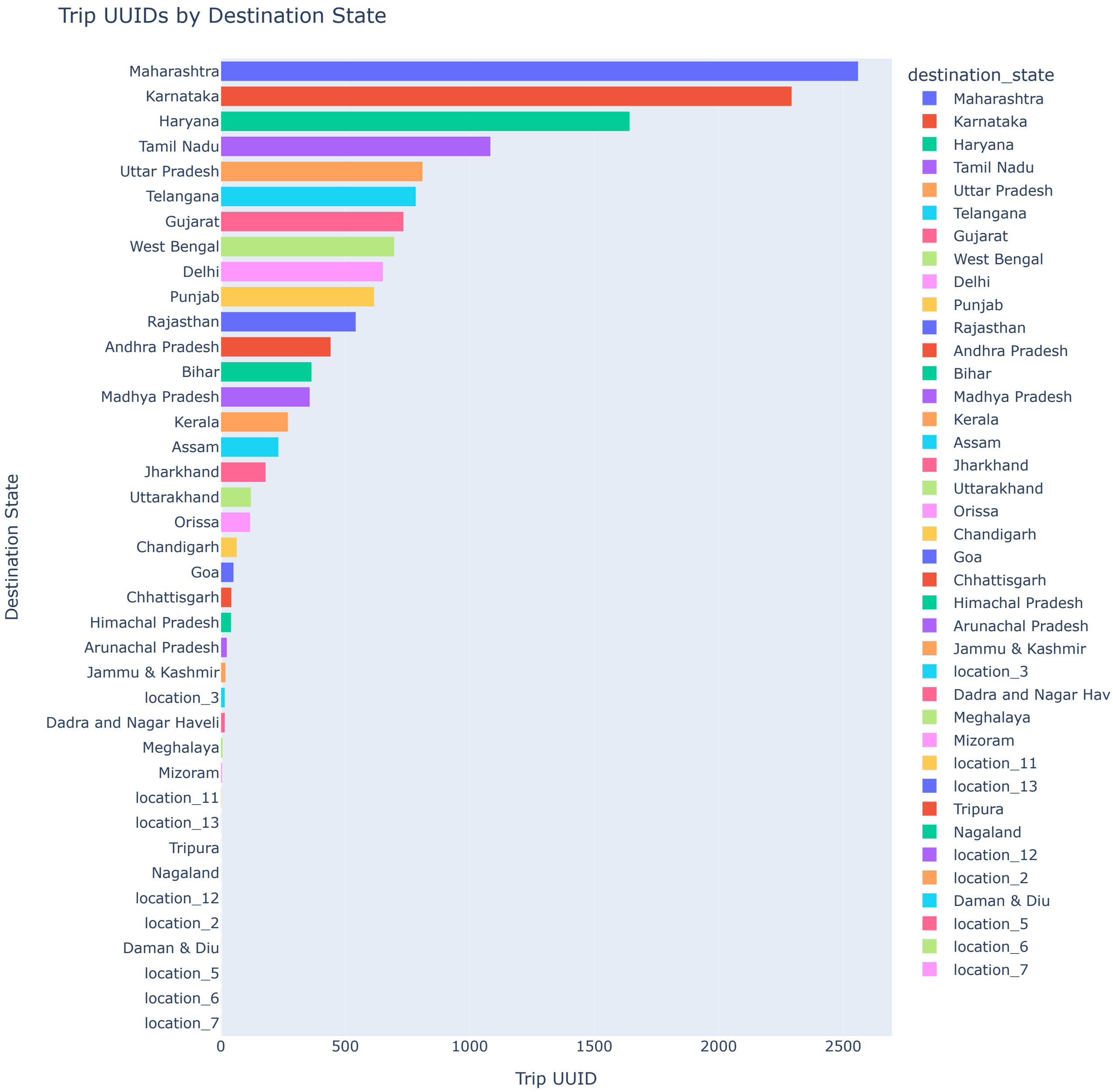
states:

In [72]:
```
df_destination_state = df2.groupby(by = 'destination_state')['trip_uuid'].count().to_frame().reset_index()
df_destination_state['perc'] = np.round(df_destination_state['trip_uuid'] * 100/ df_destination_state['trip_uuid'].sum()
df_destination_state = df_destination_state.sort_values(by = 'trip_uuid', ascending = False)
df_destination_state.head()
```

Out[72]:

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

In [73]:
```
# Sort the DataFrame by 'trip_uuid' in descending order
df_sorted_destination = df_destination_state.sort_values(by = 'trip_uuid', ascending = False)
# Create the bar chart using Plotly with a multi-color scheme
fig = px.bar(data_frame = df_sorted_destination,
             x = 'trip_uuid',          # X-axis: trip_uuid (the value for the bars)
             y = 'destination_state',  # Y-axis: destination_state (the categories for the bars)
             color = 'destination_state', # Use destination_state to assign different colors to bars
             orientation = 'h',        # Horizontal bar chart
             color_discrete_sequence = px.colors.qualitative.Plotly  # Use a qualitative color palette
            )
# Customize the layout
fig.update_layout(title = "Trip UUIDs by Destination State",
                  xaxis_title = "Trip UUID",
                  yaxis_title = "Destination State",
                  width = 950,
                  height = 950               # Adjust figure size
                 )
# Show the figure
fig.show()
```



Insights:

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

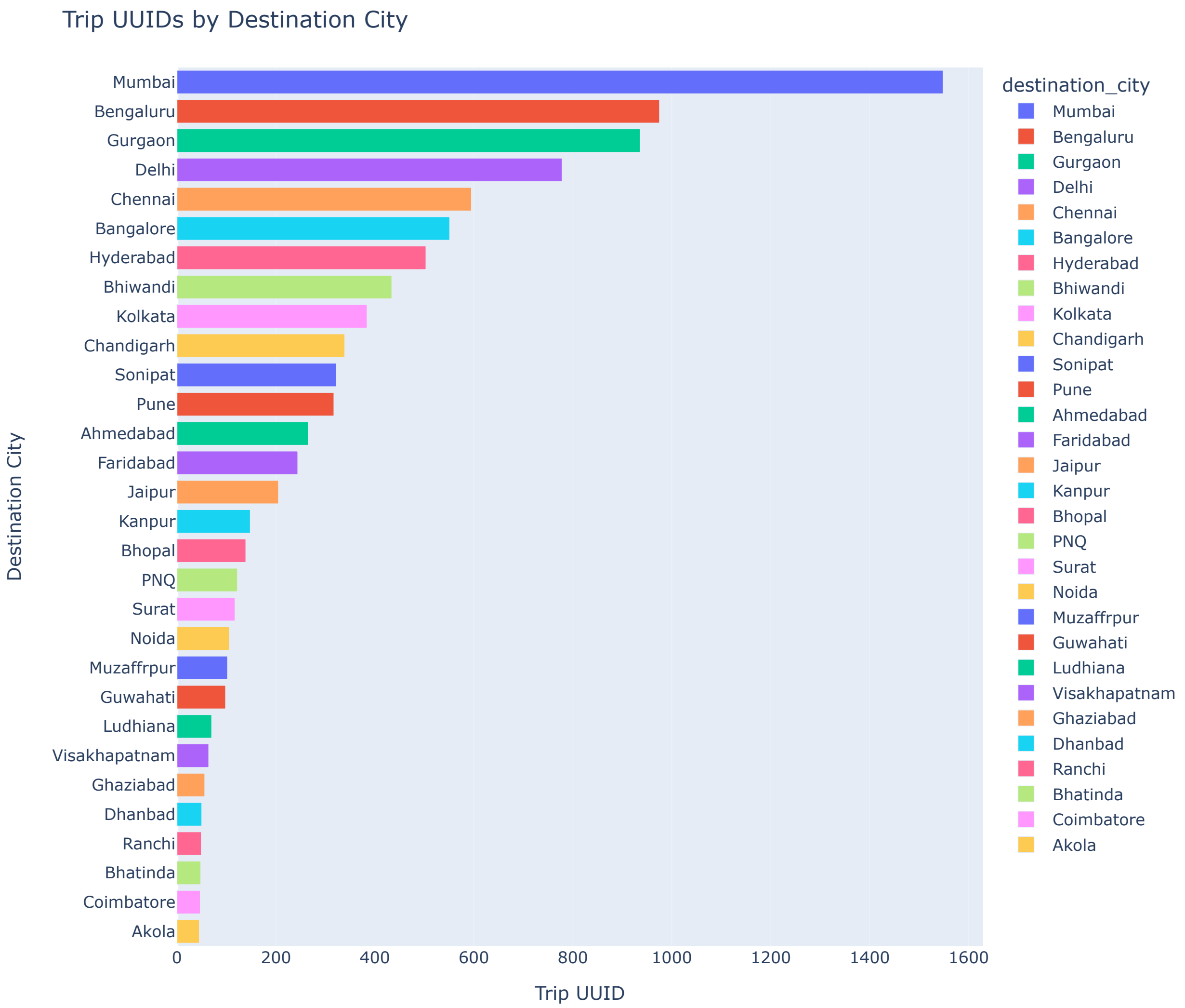
10. I am interested to know top 30 cities based on the number of trips ended in different cities:

In [74]:
```
df_destination_city = df2.groupby(by = 'destination_city')['trip_uuid'].count().to_frame().reset_index()
df_destination_city['perc'] = np.round(df_destination_city['trip_uuid'] * 100/ df_destination_city['trip_uuid'].sum(), 2
df_destination_city = df_destination_city.sort_values(by = 'trip_uuid', ascending = False)[:30]
df_destination_city.head()
```

Out[74]:

	destination_city	trip_uuid	perc
515	Mumbai	1548	10.45
96	Bengaluru	975	6.58
282	Gurgaon	936	6.32
200	Delhi	778	5.25
163	Chennai	595	4.02

In [75]:
```
# Sort the DataFrame by 'trip_uuid' in descending order
df_sorted_destination_city = df_destination_city.sort_values(by = 'trip_uuid', ascending = False)
# Create the bar chart using Plotly with a multi-color scheme
fig = px.bar(data_frame = df_sorted_destination_city,
             x = 'trip_uuid',            # X-axis: trip_uuid (the value for the bars)
             y = 'destination_city',     # Y-axis: destination_city (the categories for the bars)
             color = 'destination_city', # Use destination_city to assign different colors to bars
             orientation = 'h',          # Horizontal bar chart
             color_discrete_sequence = px.colors.qualitative.Plotly  # Use a qualitative color palette
)
# Customize the layout
fig.update_layout(title = "Trip UUIDs by Destination City",
                  xaxis_title = "Trip UUID",
                  yaxis_title = "Destination City",
                  width = 900,
                  height = 800              # Adjust figure size to (10, 10)
                 )
# Show the figure
fig.show()
```



Insights:

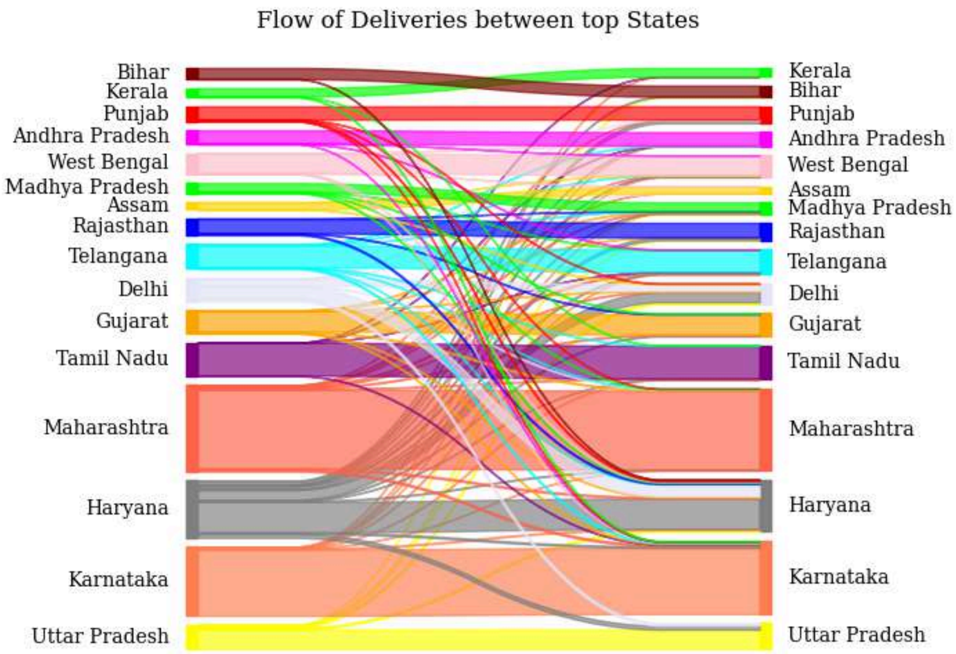
- **It can be seen in the above plot that maximum trips ended in Mumbai city followed by Bengaluru, Gurgaon, Delhi and Chennai.**
- **That means that the number of orders placed in these cities is significantly high.**

---

11. I am interested to know flow between top states:

In [76]:
```
# Flow between top states
state_colors = {
    "Karnataka": "#FF7F50",
    "Maharashtra": "#FF6347",
    "Tamil Nadu": "#800080",
    "Gujarat": "#FFA500",
    "Delhi": "#E6E6FA",
    "Haryana": "#808080",
    "Telangana": "#00FFFF",
    "Rajasthan": "#0000FF",
    "Uttar Pradesh": "#FFFF00",
    "Assam": "#FFD700",
    "Madhya Pradesh": "#00FF00",
    "West Bengal": "#FFC0CB",
    "Andhra Pradesh": "#FF00FF",
    "Punjab": "#FF0000",
    "Kerala": "#00FF00",
    "Bihar": "#800000",
}
flow = df2[(df2["source_state"].isin(state_colors.keys())) & (df2["destination_state"].isin(state_colors.keys()))][['sou
```

In [77]:
```
sankey(flow.source_state, flow.destination_state, aspect=20, colorDict=state_colors, fontsize=10)
plt.title('Flow of Deliveries between top States')
plt.show()
```



12. I am interested to know Busiest Corridors:

In [78]:
```
df2.groupby(['source_name','destination_name'])['trip_uuid'].count().sort_values(ascending=False).reset_index().head(10)
```

Out[78]:

	source_name	destination_name	trip_uuid
0	Bangalore_Nelmngla_H (Karnataka)	Bengaluru_KGAirprt_HB (Karnataka)	151
1	Gurgaon_Bilaspur_HB (Haryana)	Gurgaon_Bilaspur_HB (Haryana)	124
2	Bengaluru_Bomsndra_HB (Karnataka)	Bengaluru_KGAirprt_HB (Karnataka)	121
3	Bengaluru_KGAirprt_HB (Karnataka)	Bangalore_Nelmngla_H (Karnataka)	108
4	Bhiwandi_Mankoli_HB (Maharashtra)	Mumbai Hub (Maharashtra)	105
5	Mumbai_Chndivli_PC (Maharashtra)	Bhiwandi_Mankoli_HB (Maharashtra)	99
6	Bangalore_Nelmngla_H (Karnataka)	Bengaluru_Bomsndra_HB (Karnataka)	97
7	Muzaffrpur_Bbganj_I (Bihar)	Muzaffrpur_Bbganj_I (Bihar)	96
8	Gurgaon_Bilaspur_HB (Haryana)	Sonipat_Kundli_H (Haryana)	92
9	Bengaluru_KGAirprt_HB (Karnataka)	Bengaluru_Bomsndra_HB (Karnataka)	86

13. I am interested to know in correlation among numerical columns:

In [79]:
```
numerical_columns = ['od_total_time', 'start_scan_to_end_scan', 'actual_distance_to_destination',
                     'actual_time', 'osrm_time', 'osrm_distance', 'segment_actual_time',
                     'segment_osrm_time', 'segment_osrm_distance']
sns.pairplot(data = df2,
             vars = numerical_columns,
             kind = 'reg',
             hue = 'route_type',
             markers = '.')
plt.plot()
```

Out[79]: []

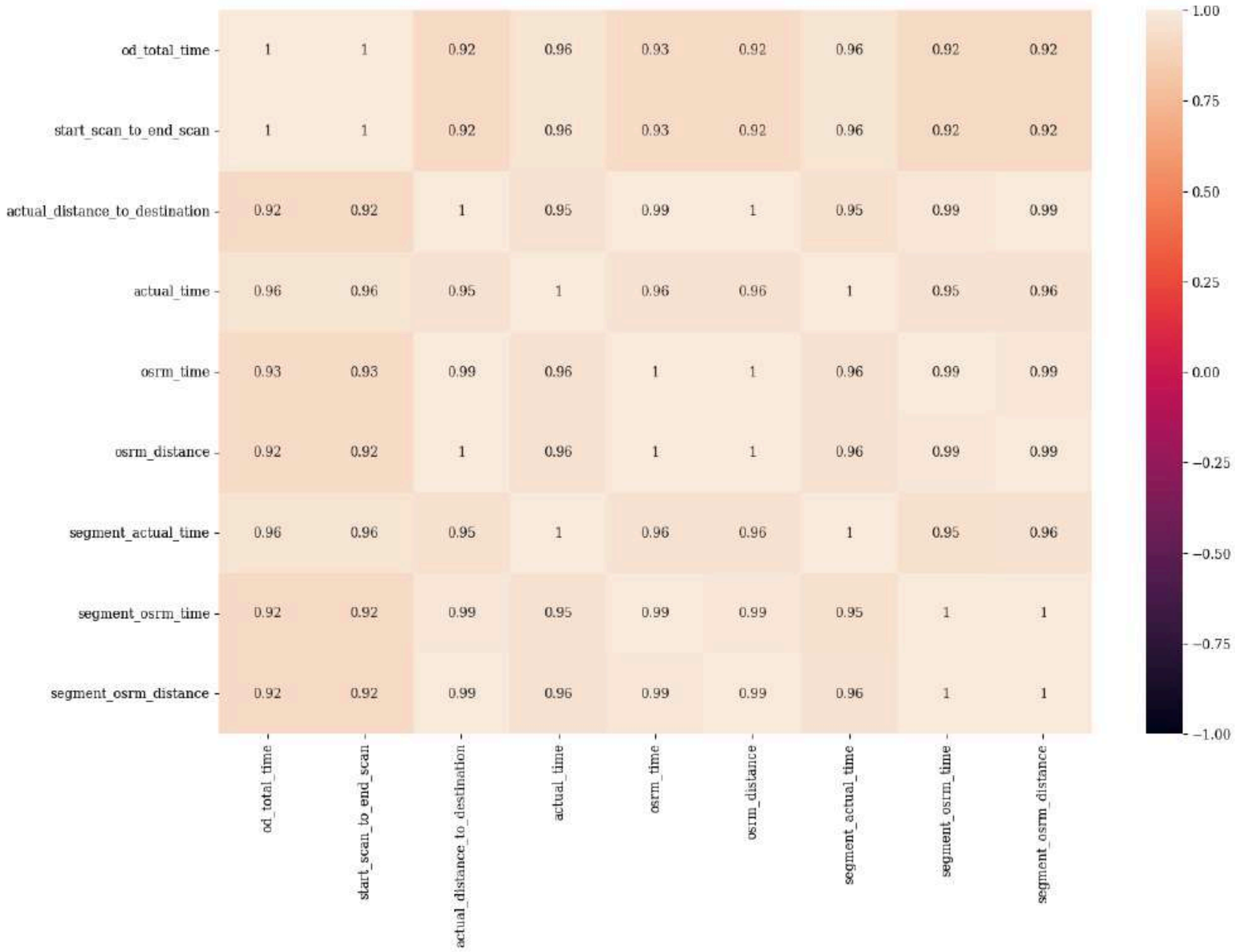
In [80]:
```
df_corr = df2[numerical_columns].corr()
df_corr
```

Out[80]:

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

In [81]:
```
plt.figure(figsize = (15, 10))
sns.heatmap(data = df_corr,
            vmin = -1,
            vmax = 1,
            annot = True)
plt.plot()
```

Out[81]: []



Insights:

- **Very High Correlation (> 0.9) exists between columns all the numerical columns specified above.**

---

3. In-depth analysis and feature engineering:

A. Compare the difference between Point a. and start_scan_to_end_scan. Do hypothesis testing/ Visual analysis to check.

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

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

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

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

F. Find outliers in the numerical variables (you might find outliers in almost all the variables), and check it using visual analysis.

G. Handle the outliers using the IQR method.

H. Do one-hot encoding of categorical variables (like route_type).

I. Normalize/ Standardize the numerical features using MinMaxScaler or StandardScale.

3A. Comparing the difference between od_total_time and start_scan_to_end_scan.

Doing hypothesis testing/ Visual analysis to check:

STEP-1 : Set up Null Hypothesis

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

STEP-2 : Checking for basic assumpitons for the hypothesis

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

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

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

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

- We set our ***alpha to be 0.05***

STEP-5 : Compare p-value and alpha.

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

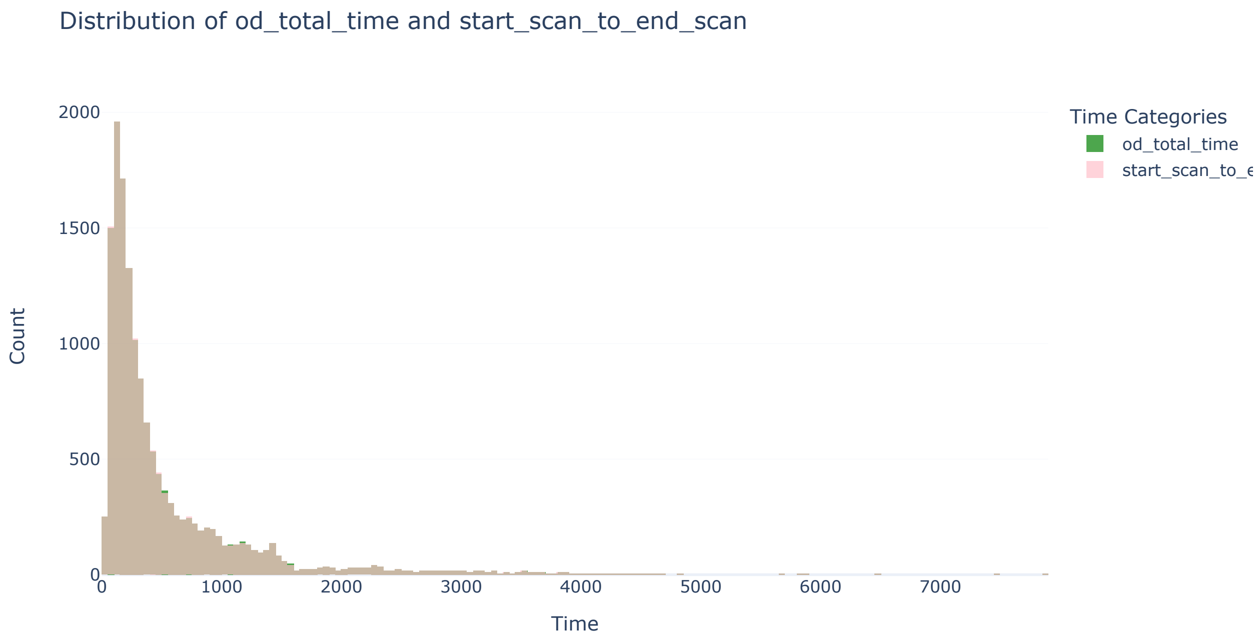
   1. **p-val > alpha** : Accept H0
   2. **p-val < alpha** : Reject H0

In [82]:
```
df2[['od_total_time', 'start_scan_to_end_scan']].describe()
```
Out[82]:

	od_total_time	start_scan_to_end_scan
count	14817.000000	14817.000000
mean	531.697630	530.810016
std	658.868223	658.705957
min	23.460000	23.000000
25%	149.930000	149.000000
50%	280.770000	280.000000
75%	638.200000	637.000000
max	7898.550000	7898.000000

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

In [83]:
```
# Create histogram for 'od_total_time'
hist1 = go.Histogram(x = df2['od_total_time'],
                     name = 'od_total_time',
                     marker_color = 'green',
                     opacity = 0.7
                    )
# Create histogram for 'start_scan_to_end_scan'
hist2 = go.Histogram(x = df2['start_scan_to_end_scan'],
                     name = 'start_scan_to_end_scan',
                     marker_color = 'pink',
                     opacity = 0.7
                    )
# Create the figure
fig = go.Figure(data = [hist1, hist2])
# Update layout
fig.update_layout(barmode = 'overlay',
                  xaxis_title = 'Time',
                  yaxis_title = 'Count',
                  legend_title = 'Time Categories',
                  title = 'Distribution of od_total_time and start_scan_to_end_scan',
                  template = 'plotly_white'
                 )
# Show the plot
fig.show()
```



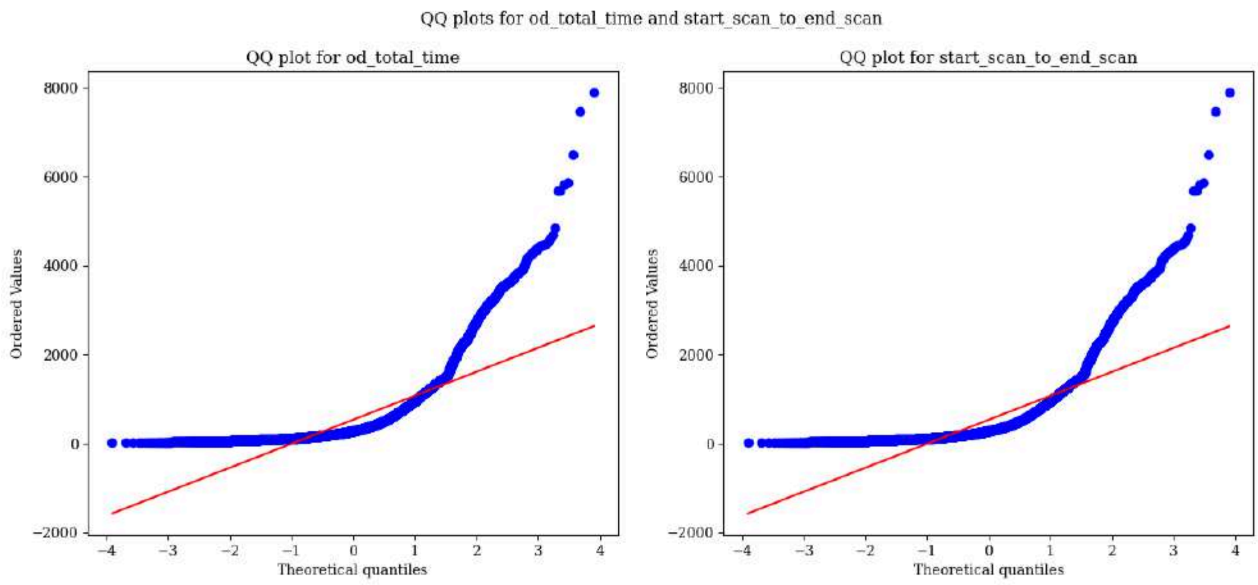
Insights:

- **It can be seen from the above plot that the data does not follow normal distribution.**

Distribution check using QQ Plot:

In [84]:
```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for od_total_time and start_scan_to_end_scan')
spy.probplot(df2['od_total_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for od_total_time')
plt.subplot(1, 2, 2)
spy.probplot(df2['start_scan_to_end_scan'], plot = plt, dist = 'norm')
plt.title('QQ plot for start_scan_to_end_scan')
plt.plot()
```

Out[84]: []



Insights:

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

Applying Shapiro-Wilk test for normality:

: The sample **follows normal distribution**
: The sample **does not follow normal distribution**

alpha = 0.05

Test Statistics : **Shapiro-Wilk test for normality**

In [85]:
```
test_stat, p_value = spy.shapiro(df2['od_total_time'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

In [86]:
```
test_stat, p_value = spy.shapiro(df2['start_scan_to_end_scan'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

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

In [87]:
```
transformed_od_total_time = spy.boxcox(df2['od_total_time'])[0]
test_stat, p_value = spy.shapiro(transformed_od_total_time)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 7.172770042757021e-25
The sample does not follow normal distribution
```

In [88]:
```
transformed_start_scan_to_end_scan = spy.boxcox(df2['start_scan_to_end_scan'])[0]
test_stat, p_value = spy.shapiro(transformed_start_scan_to_end_scan)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 1.0471322892609475e-24
The sample does not follow normal distribution
```

Insights:

- **Even after applying the boxcox transformation on each of the "od_total_time" and "start_scan_to_end_scan" columns, the distributions do not follow normal distribution.**

Checking homogeneity of Variances using Lavene's test:

In [89]:
```
# Null Hypothesis(H0) - Homogenous Variance
# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = spy.levene(df2['od_total_time'], df2['start_scan_to_end_scan'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples do not have  Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 0.9668007217581142
The samples have Homogenous Variance
```

Since the samples are not normally distributed, T-Test cannot be applied here, we can perform its non parametric equivalent

test i.e., Mann-Whitney U rank test for two independent samples:

In [90]:
```
test_stat, p_value = spy.mannwhitneyu(df2['od_total_time'], df2['start_scan_to_end_scan'])
print('P-value :',p_value)
```

```
P-value : 0.7815123224221716
```

Insights:

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

3B. Doing hypothesis testing / visual analysis between actual_time aggregated

value and OSRM time aggregated value (aggregated values are the values we will

get after merging the rows on the basis of trip_uuid)

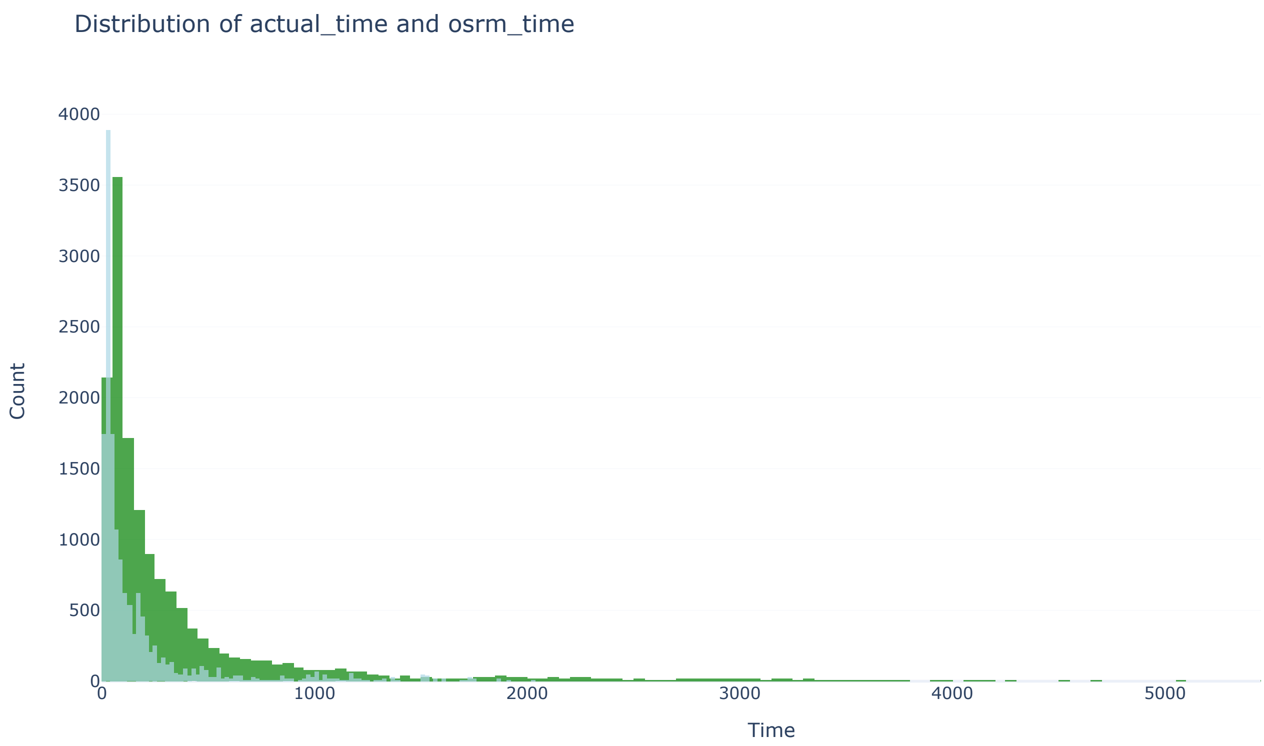
In [91]:
```
df2[['actual_time', 'osrm_time']].describe()
```

Out[91]:

	actual_time	osrm_time
count	14817.000000	14817.000000
mean	357.143754	161.384018
std	561.396157	271.360995
min	9.000000	6.000000
25%	67.000000	29.000000
50%	149.000000	60.000000
75%	370.000000	168.000000
max	6265.000000	2032.000000

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

In [92]:
```
# Create histogram for 'actual_time'
hist1 = go.Histogram(x = df2['actual_time'],
                     name = 'actual_time',
                     marker_color = 'green',
                     opacity = 0.7
                    )
# Create histogram for 'osrm_time'
hist2 = go.Histogram(x = df2['osrm_time'],
                     name = 'osrm_time',
                     marker_color = 'lightblue',
                     opacity = 0.7
                    )
# Create the figure
fig = go.Figure(data = [hist1, hist2])
# Update layout
fig.update_layout(barmode = 'overlay',  # Overlay histograms
                  xaxis_title = 'Time',
                  yaxis_title = 'Count',
                  legend_title = 'Time Categories',
                  title = 'Distribution of actual_time and osrm_time',
                  template = 'plotly_white',
                  width = 1200,  # Setting the figure size
                  height = 600
                 )
# Show the plot
fig.show()
```



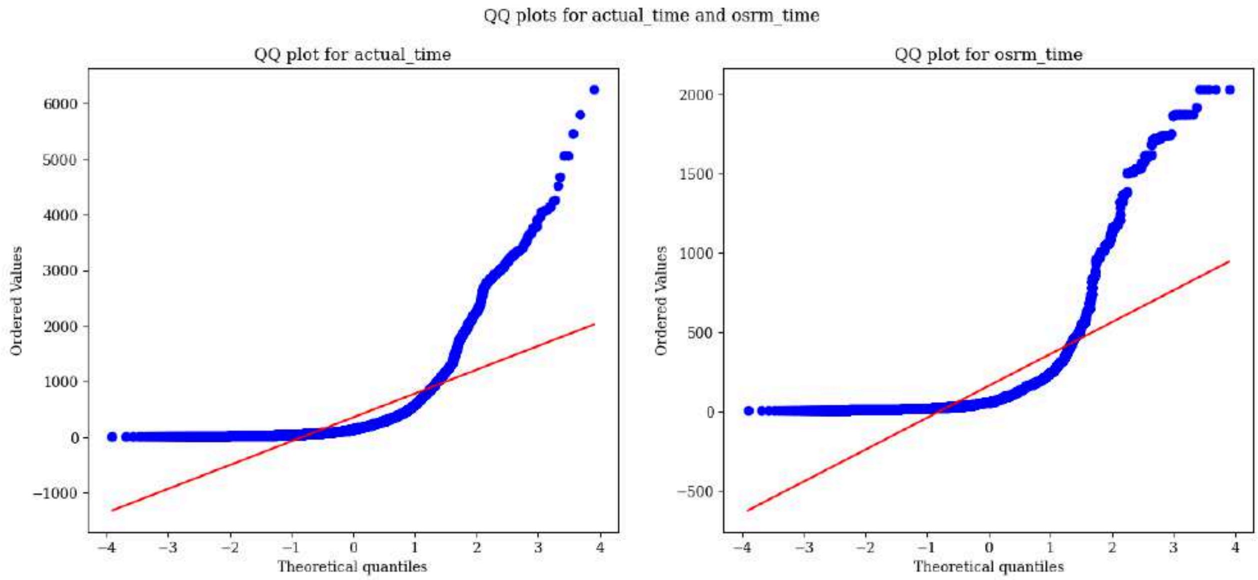
Insights:

- **It can be seen from the above plot that the data does not follow normal distribution.**

Distribution check using QQ Plot:

In [93]:
```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for actual_time and osrm_time')
spy.probplot(df2['actual_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for actual_time')
plt.subplot(1, 2, 2)
spy.probplot(df2['osrm_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for osrm_time')
plt.plot()
```

Out[93]: []



Insights:

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

Applying Shapiro-Wilk test for normality:

: The sample **follows normal distribution**
: The sample **does not follow normal distribution**

alpha = 0.05

Test Statistics : **Shapiro-Wilk test for normality**

In [94]:
```
test_stat, p_value = spy.shapiro(df2['actual_time'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

In [95]:
```
test_stat, p_value = spy.shapiro(df2['osrm_time'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

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

In [96]:
```
transformed_actual_time = spy.boxcox(df2['actual_time'])[0]
test_stat, p_value = spy.shapiro(transformed_actual_time)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 1.021792743086169e-28
The sample does not follow normal distribution
```

In [97]:
```
transformed_osrm_time = spy.boxcox(df2['osrm_time'])[0]
test_stat, p_value = spy.shapiro(transformed_osrm_time)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 3.543600614978861e-35
The sample does not follow normal distribution
```

Insights:

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

Checking homogeneity of Variances using Lavene's test:

In [98]:
```
# Null Hypothesis(H0) - Homogenous Variance
# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = spy.levene(df2['actual_time'], df2['osrm_time'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples do not have  Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 1.871297993683208e-220
The samples do not have  Homogenous Variance
```

Since the samples are not normally distributed, T-Test cannot be applied here, we can perform its non parametric equivalent

test i.e., Mann-Whitney U rank test for two independent samples:

In [99]:
```
test_stat, p_value = spy.mannwhitneyu(df2['actual_time'], df2['osrm_time'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples are not similar')
else:
    print('The samples are similar ')
```

```
p-value 0.0
The samples are not similar
```

Insights:

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

3C. Do hypothesis testing/ visual analysis between actual_time aggregated value

and segment actual time aggregated value (aggregated values are the values we

will get after merging the rows on the basis of trip_uuid):

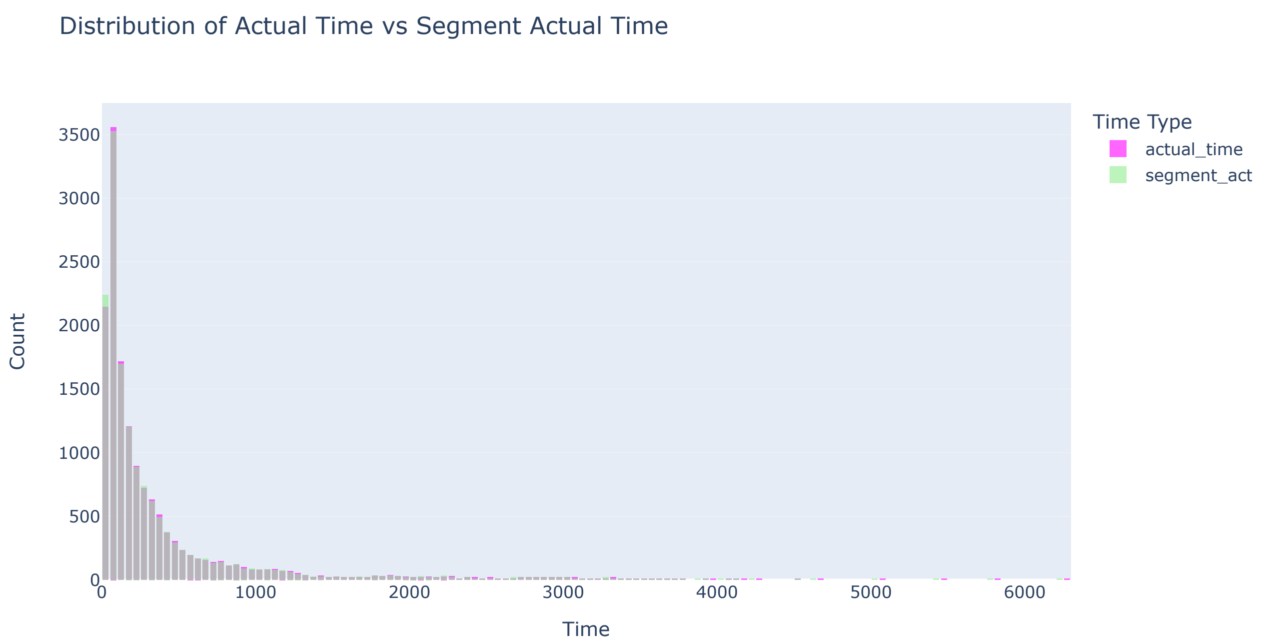
In [100]:
```
df2[['actual_time', 'segment_actual_time']].describe()
```

Out[100]:

	actual_time	segment_actual_time
count	14817.000000	14817.000000
mean	357.143754	353.892286
std	561.396157	556.247965
min	9.000000	9.000000
25%	67.000000	66.000000
50%	149.000000	147.000000
75%	370.000000	367.000000
max	6265.000000	6230.000000

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

In [101]:
```
fig = go.Figure()
# Adding histogram for 'actual_time'
fig.add_trace(go.Histogram(x = df2['actual_time'],
                           name = 'actual_time',
                           marker_color = 'magenta',
                           opacity = 0.75
                          )
             )
# Adding histogram for 'segment_actual_time'
fig.add_trace(go.Histogram(x = df2['segment_actual_time'],
                           name = 'segment_actual_time',
                           marker_color = 'lightgreen',
                           opacity = 0.75
                          )
             )
# Overlay both histograms
fig.update_layout(barmode = 'overlay',
                  title = 'Distribution of Actual Time vs Segment Actual Time',
                  xaxis_title = 'Time',
                  yaxis_title = 'Count',
                  legend_title = 'Time Type',
                  bargap = 0.2,
                  bargroupgap = 0.1
                 )
# Update the layout and show the figure
fig.update_traces(opacity = 0.6)
fig.show()
```



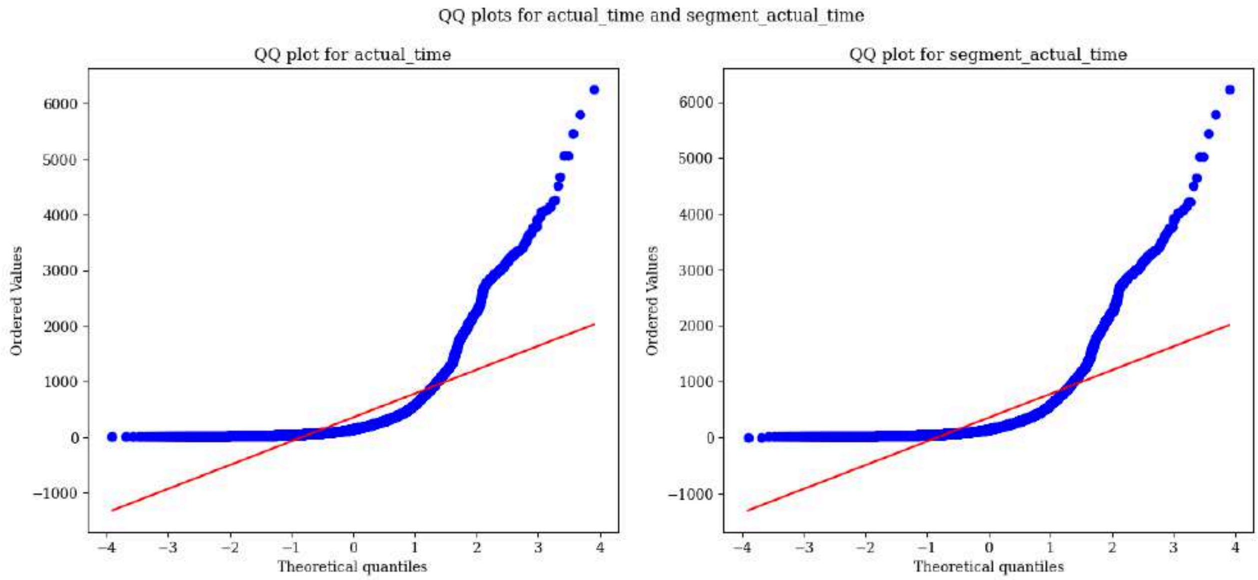
Insights:

- **It can be seen from the above plot that the data does not follow normal distribution.**

Distribution check using QQ Plot:

In [102]:
```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for actual_time and segment_actual_time')
spy.probplot(df2['actual_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for actual_time')
plt.subplot(1, 2, 2)
spy.probplot(df2['segment_actual_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_actual_time')
plt.plot()
```

Out[102]: []



Insights:

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

Applying Shapiro-Wilk test for normality:

: The sample **follows normal distribution**
: The sample **does not follow normal distribution**

alpha = 0.05

Test Statistics : **Shapiro-Wilk test for normality**

In [103]:
```
test_stat, p_value = spy.shapiro(df2['actual_time'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

In [104]:
```
test_stat, p_value = spy.shapiro(df2['segment_actual_time'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

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

In [105]:
```
transformed_actual_time = spy.boxcox(df2['actual_time'])[0]
test_stat, p_value = spy.shapiro(transformed_actual_time)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 1.021792743086169e-28
The sample does not follow normal distribution
```

In [106]:
```
transformed_segment_actual_time = spy.boxcox(df2['segment_actual_time'])[0]
test_stat, p_value = spy.shapiro(transformed_segment_actual_time)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 5.696120172016859e-29
The sample does not follow normal distribution
```

Insights:

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

Checking homogeneity of Variances using Lavene's test:

In [107]:
```
# Null Hypothesis(H0) - Homogenous Variance
# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = spy.levene(df2['actual_time'], df2['segment_actual_time'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples do not have Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 0.6955022668700895
The samples have Homogenous Variance
```

Since the samples are not normally distributed, T-Test cannot be applied here, we can perform its non parametric equivalent

test i.e., Mann-Whitney U rank test for two independent samples:

In [108]:
```
test_stat, p_value = spy.mannwhitneyu(df2['actual_time'], df2['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 0.4164235159622476
The samples are similar
```

Insights:

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

3D. Do hypothesis testing/ visual analysis between osrm distance aggregated value and segment osrm distance aggregated value (aggregated values are the values we will get after merging the rows on the basis of trip_uuid):

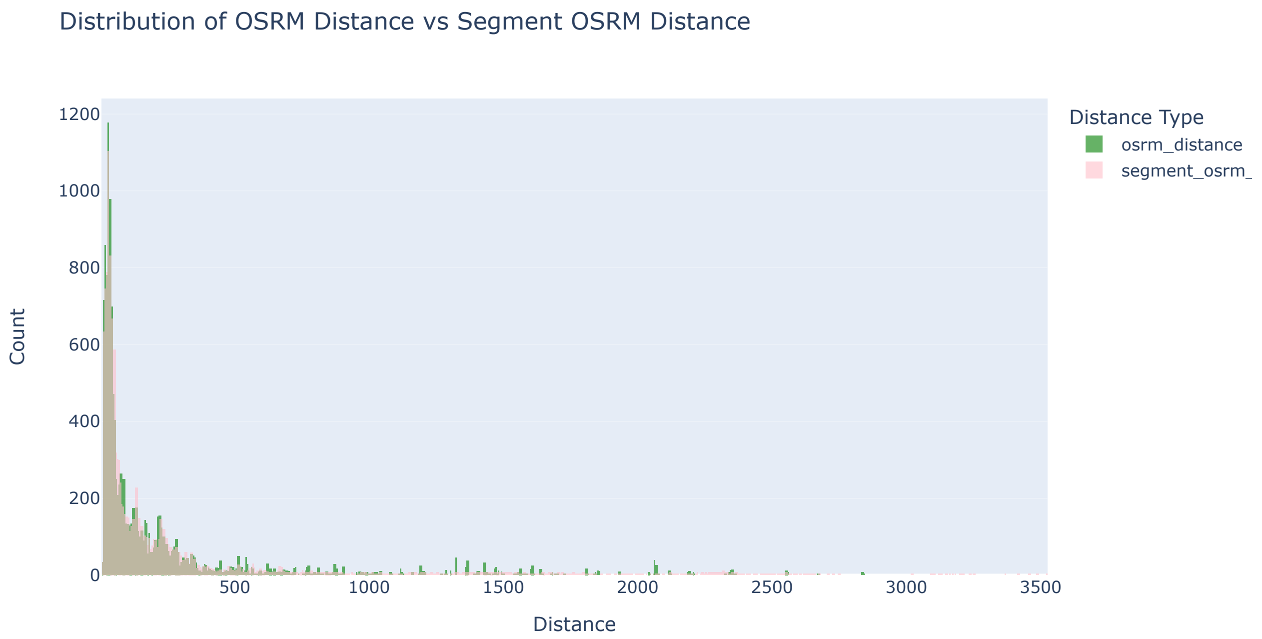
In [109]:
```
df2[['osrm_distance', 'segment_osrm_distance']].describe()
```

Out[109]:

	osrm_distance	segment_osrm_distance
count	14817.000000	14817.000000
mean	204.344689	223.201161
std	370.395573	416.628374
min	9.072900	9.072900
25%	30.819200	32.654500
50%	65.618800	70.154400
75%	208.475000	218.802400
max	2840.081000	3523.632400

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

In [110]:
```
fig = go.Figure()
# Adding histogram for 'osrm_distance'
fig.add_trace(go.Histogram(x = df2['osrm_distance'],
                           name = 'osrm_distance',
                           marker_color = 'green',
                           nbinsx = 1000,
                           opacity = 0.75
                          )
             )
# Adding histogram for 'segment_osrm_distance'
fig.add_trace(go.Histogram(x = df2['segment_osrm_distance'],
                           name = 'segment_osrm_distance',
                           marker_color = 'pink',
                           nbinsx = 1000,
                           opacity = 0.75
                          )
             )
# Overlay both histograms
fig.update_layout(barmode = 'overlay',
                  title = 'Distribution of OSRM Distance vs Segment OSRM Distance',
                  xaxis_title = 'Distance',
                  yaxis_title = 'Count',
                  legend_title = 'Distance Type',
                  bargap = 0.2,
                  bargroupgap = 0.1
                 )
# Update the layout and show the figure
fig.update_traces(opacity = 0.6)
fig.show()
```



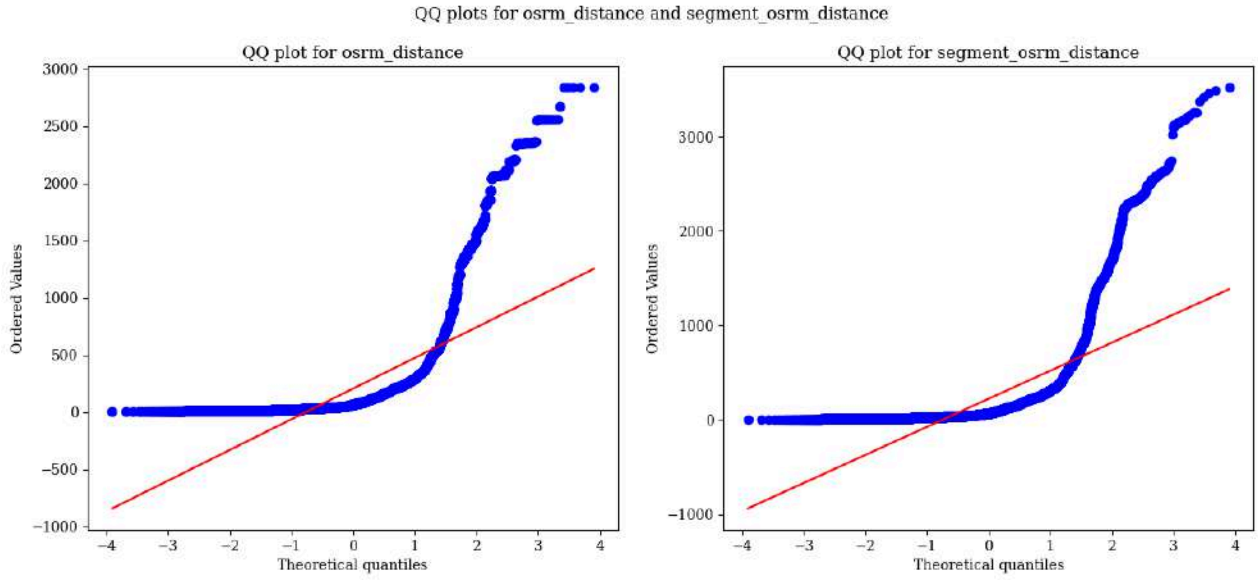
Insights:

- **It can be seen from the above plot that the data does not follow normal distribution.**

Distribution check using QQ Plot:

In [111]:
```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for osrm_distance and segment_osrm_distance')
spy.probplot(df2['osrm_distance'], plot = plt, dist = 'norm')
plt.title('QQ plot for osrm_distance')
plt.subplot(1, 2, 2)
spy.probplot(df2['segment_osrm_distance'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_osrm_distance')
plt.plot()
```

Out[111]: []



Insights:

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

Applying Shapiro-Wilk test for normality:

: The sample **follows normal distribution**
: The sample **does not follow normal distribution**

alpha = 0.05

Test Statistics : **Shapiro-Wilk test for normality**

In [112]:
```
test_stat, p_value = spy.shapiro(df2['osrm_distance'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

In [113]:
```
test_stat, p_value = spy.shapiro(df2['segment_osrm_distance'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

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

In [114]:
```
transformed_osrm_distance = spy.boxcox(df2['osrm_distance'])[0]
test_stat, p_value = spy.shapiro(transformed_osrm_distance)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 7.114532433223529e-41
The sample does not follow normal distribution
```

In [115]:
```
transformed_segment_osrm_distance = spy.boxcox(df2['segment_osrm_distance'])[0]
test_stat, p_value = spy.shapiro(transformed_segment_osrm_distance)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 3.0623432935550394e-38
The sample does not follow normal distribution
```

Insights:

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

Checking homogeneity of Variances using Lavene's test:

In [116]:
```
# Null Hypothesis(H0) - Homogenous Variance
# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = spy.levene(df2['osrm_distance'], df2['segment_osrm_distance'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples do not have Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 0.00020976354422600578
The samples do not have Homogenous Variance
```

Since the samples are not normally distributed, T-Test cannot be applied here, we can perform its non parametric equivalent

test i.e., Mann-Whitney U rank test for two independent samples:

In [117]:
```
test_stat, p_value = spy.mannwhitneyu(df2['osrm_distance'], df2['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 9.511383588276373e-07
The samples are not similar
```

Insights:

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

3E. Do hypothesis testing/ visual analysis between osrm time aggregated value

and segment osrm time aggregated value (aggregated values are the values we will

get after merging the rows on the basis of trip_uuid):

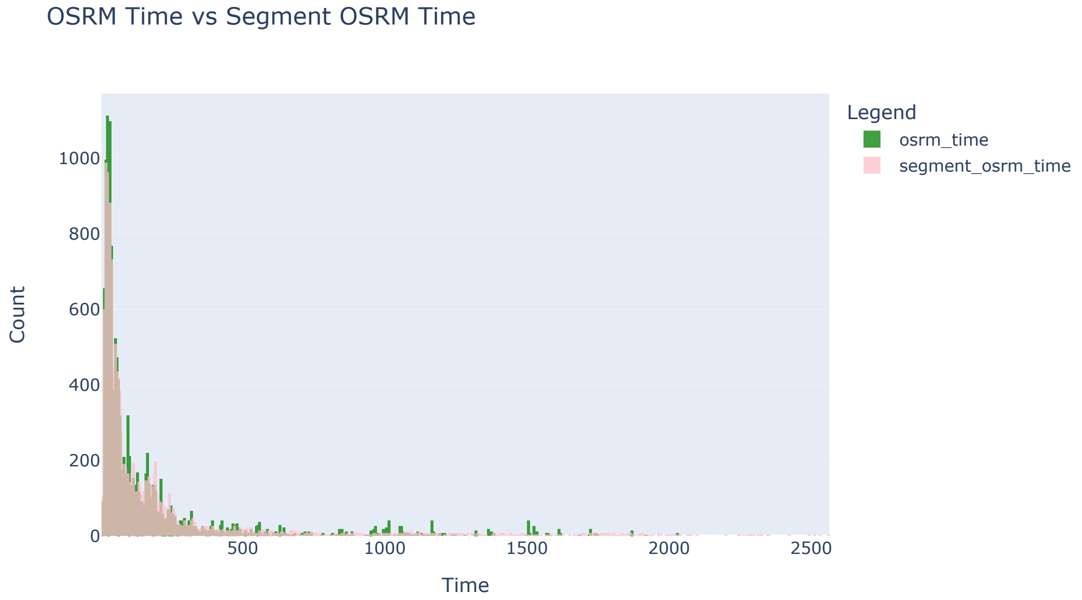
In [118]:
```
df2[['osrm_time', 'segment_osrm_time']].describe().T
```

Out[118]:

	count	mean	std	min	25%	50%	75%	max
osrm_time	14817.0	161.384018	271.360995	6.0	29.0	60.0	168.0	2032.0
segment_osrm_time	14817.0	180.949787	314.542047	6.0	31.0	65.0	185.0	2564.0

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

In [119]:
```
# Create a histogram for 'osrm_time'
fig = go.Figure()
# Add histogram for 'osrm_time'
fig.add_trace(go.Histogram(x = df2['osrm_time'],
                           nbinsx = 1000,
                           name = 'osrm_time',
                           marker_color = 'green',
                           opacity = 0.75
                          )
             )
# Add histogram for 'segment_osrm_time'
fig.add_trace(go.Histogram(x = df2['segment_osrm_time'],
                           nbinsx = 1000,
                           name = 'segment_osrm_time',
                           marker_color = 'pink',
                           opacity = 0.75
                          )
             )
# Update Layout
fig.update_layout(barmode = 'overlay',
                  xaxis_title = 'Time',
                  yaxis_title = 'Count',
                  legend = dict(title='Legend'),
                  title = 'OSRM Time vs Segment OSRM Time',
                  width = 800,
                  height = 500
                 )
# Display the plot
fig.show()
```



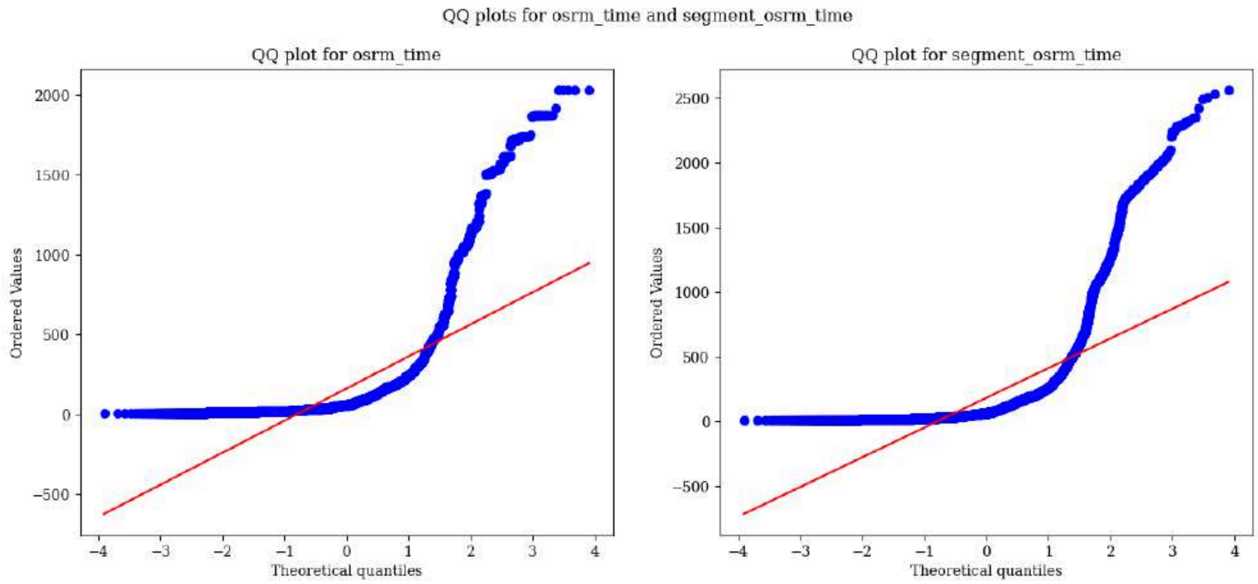
Insights:

- **It can be seen from the above plot that the data does not follow normal distribution.**

Distribution check using QQ Plot:

In [120]:
```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for osrm_time and segment_osrm_time')
spy.probplot(df2['osrm_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for osrm_time')
plt.subplot(1, 2, 2)
spy.probplot(df2['segment_osrm_time'], plot = plt, dist = 'norm')
plt.title('QQ plot for segment_osrm_time')
plt.plot()
```

Out[120]: []



Insights:

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

Applying Shapiro-Wilk test for normality:

: The sample **follows normal distribution**
: The sample **does not follow normal distribution**

alpha = 0.05

Test Statistics : **Shapiro-Wilk test for normality**

In [121]:
```
test_stat, p_value = spy.shapiro(df2['osrm_time'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

In [122]:
```
test_stat, p_value = spy.shapiro(df2['segment_osrm_time'].sample(5000))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

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

In [123]:
```
transformed_osrm_time = spy.boxcox(df2['osrm_time'])[0]
test_stat, p_value = spy.shapiro(transformed_osrm_time)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 3.543600614978861e-35
The sample does not follow normal distribution
```

In [124]:
```
transformed_segment_osrm_time = spy.boxcox(df2['segment_osrm_time'])[0]
test_stat, p_value = spy.shapiro(transformed_segment_osrm_time)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 4.8932509971545 72e-34
The sample does not follow normal distribution
```

Insights:

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

Checking homogeneity of Variances using Lavene's test:

In [125]:
```
# Null Hypothesis(H0) - Homogenous Variance
# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = spy.levene(df2['osrm_time'], df2['segment_osrm_time'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples do not have Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 8.349482669010088e-08
The samples do not have Homogenous Variance
```

Since the samples are not normally distributed, T-Test cannot be applied here, we can perform its non parametric equivalent

test i.e., Mann-Whitney U rank test for two independent samples:

In [126]:
```
test_stat, p_value = spy.mannwhitneyu(df2['osrm_time'], df2['segment_osrm_time'])
print('p-value', p_value)
if p_value < 0.05:
    print('The samples are not similar')
else:
    print('The samples are similar ')
```

```
p-value 2.2995370859748865e-08
The samples are not similar
```

Insights:

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

3F. Find outliers in the numerical variables (you might find outliers in almost

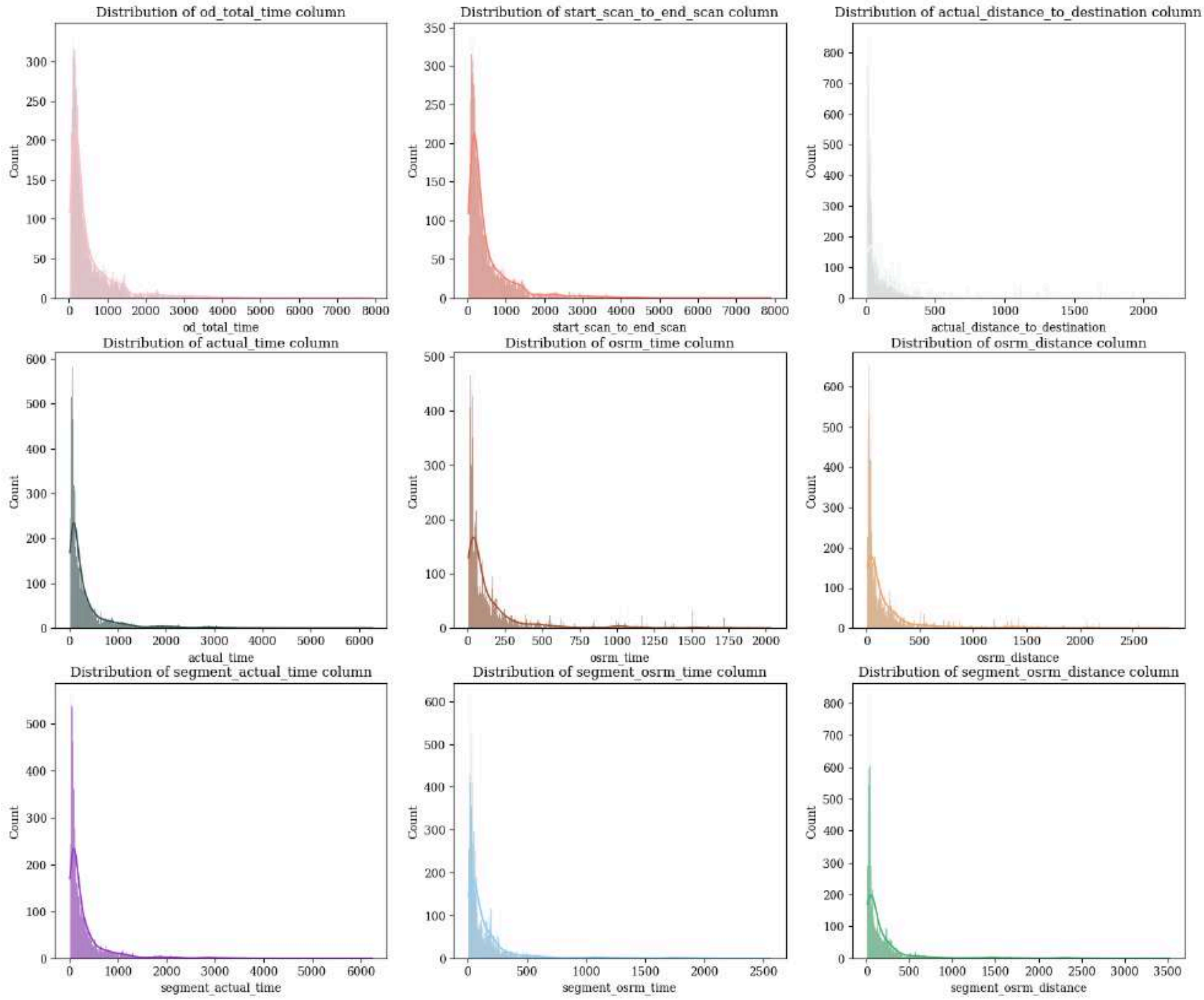
all the variables), and check it using visual analysis:

In [127]:
```
numerical_columns = ['od_total_time', 'start_scan_to_end_scan', 'actual_distance_to_destination',
                     'actual_time', 'osrm_time', 'osrm_distance', 'segment_actual_time',
                     'segment_osrm_time', 'segment_osrm_distance']
df2[numerical_columns].describe().T
```

Out[127]:

	count	mean	std	min	25%	50%	75%	max
od_total_time	14817.0	531.697630	658.868223	23.460000	149.930000	280.770000	638.200000	7898.550000
start_scan_to_end_scan	14817.0	530.810016	658.705957	23.000000	149.000000	280.000000	637.000000	7898.000000
actual_distance_to_destination	14817.0	164.477838	305.388147	9.002461	22.837239	48.474072	164.583208	2186.531787
actual_time	14817.0	357.143754	561.396157	9.000000	67.000000	149.000000	370.000000	6265.000000
osrm_time	14817.0	161.384018	271.360995	6.000000	29.000000	60.000000	168.000000	2032.000000
osrm_distance	14817.0	204.344689	370.395573	9.072900	30.819200	65.618800	208.475000	2840.081000
segment_actual_time	14817.0	353.892286	556.247965	9.000000	66.000000	147.000000	367.000000	6230.000000
segment_osrm_time	14817.0	180.949787	314.542047	6.000000	31.000000	65.000000	185.000000	2564.000000
segment_osrm_distance	14817.0	223.201161	416.628374	9.072900	32.654500	70.154400	218.802400	3523.632400

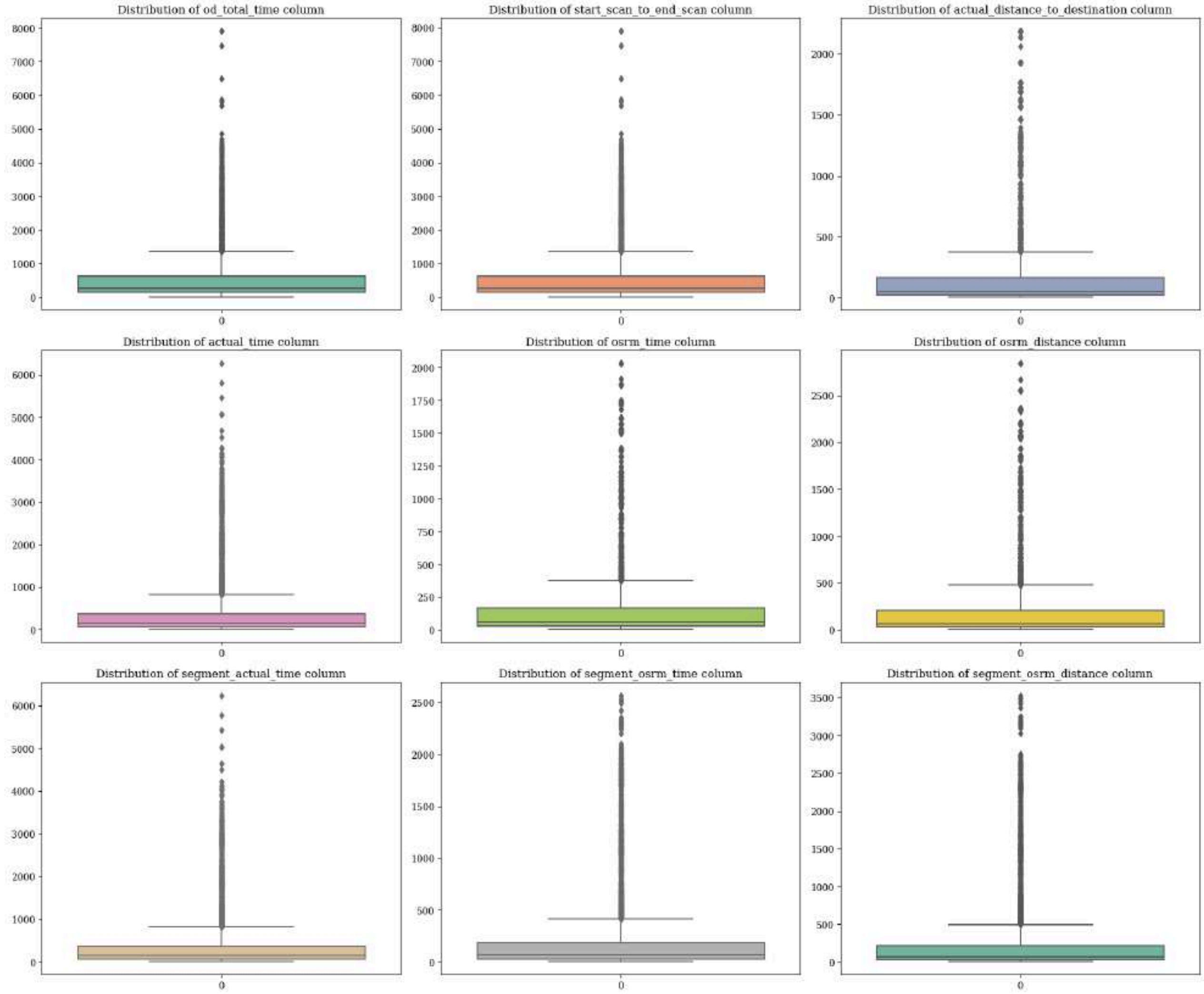
In [128]:
```
plt.figure(figsize = (18, 15))
for i in range(len(numerical_columns)):
    plt.subplot(3, 3, i + 1)
    clr = np.random.choice(list(mpl.colors.cnames))
    sns.histplot(df2[numerical_columns[i]], bins = 1000, kde = True, color = clr)
    plt.title(f"Distribution of {numerical_columns[i]} column")
    plt.plot()
```



Insights:

- **It can be inferred from the above plots that data in all the numerical columns are right skewed.**

In [129]:
```
plt.figure(figsize=(18, 15))
# Use a nice color palette from seaborn (e.g., 'Set2', 'Paired', 'muted', etc.)
palette = sns.color_palette('Set2', len(numerical_columns))
for i in range(len(numerical_columns)):
    plt.subplot(3, 3, i + 1)
    clr = palette[i]  # Assign a color from the selected palette
    sns.boxplot(df2[numerical_columns[i]], color=clr)
    plt.title(f"Distribution of {numerical_columns[i]} column")
plt.tight_layout()
plt.show()
```



Insights:

- **It can be clearly seen in the above plots that there are outliers in all the numerical columns that need to be treated.**

In [130]:
```
# Detecting Outliers
for i in numerical_columns:
    Q1 = np.quantile(df2[i], 0.25)
    Q3 = np.quantile(df2[i], 0.75)
    IQR = Q3 - Q1
    LB = Q1 - 1.5 * IQR
    UB = Q3 + 1.5 * IQR
    outliers = df2.loc[(df2[i] < LB) | (df2[i] > UB)]
    print('Column :', i)
    print(f'Q1 : {Q1}')
    print(f'Q3 : {Q3}')
    print(f'IQR : {IQR}')
    print(f'LB : {LB}')
    print(f'UB : {UB}')
    print(f'Number of outliers : {outliers.shape[0]}')
    print('----------------------------------')
```

```
Column : od_total_time
Q1 : 149.93
Q3 : 638.2
IQR : 488.27000000000004
LB : -582.4750000000001
UB : 1370.605
Number of outliers : 1266
----------------------------------
Column : start_scan_to_end_scan
Q1 : 149.0
Q3 : 637.0
IQR : 488.0
LB : -583.0
UB : 1369.0
Number of outliers : 1267
----------------------------------
Column : actual_distance_to_destination
Q1 : 22.83723905859321
Q3 : 164.58320763841138
IQR : 141.74596857981817
LB : -189.78171381113404
UB : 377.2021605081386
Number of outliers : 1449
----------------------------------
Column : actual_time
Q1 : 67.0
Q3 : 370.0
IQR : 303.0
LB : -387.5
UB : 824.5
Number of outliers : 1643
----------------------------------
Column : osrm_time
Q1 : 29.0
Q3 : 168.0
IQR : 139.0
LB : -179.5
UB : 376.5
Number of outliers : 1517
----------------------------------
Column : osrm_distance
Q1 : 30.8192
Q3 : 208.475
IQR : 177.6558
LB : -235.6645
UB : 474.9587
Number of outliers : 1524
----------------------------------
Column : segment_actual_time
Q1 : 66.0
Q3 : 367.0
IQR : 301.0
LB : -385.5
UB : 818.5
Number of outliers : 1643
----------------------------------
Column : segment_osrm_time
Q1 : 31.0
Q3 : 185.0
IQR : 154.0
LB : -200.0
UB : 416.0
Number of outliers : 1492
----------------------------------
Column : segment_osrm_distance
Q1 : 32.6545
Q3 : 218.8024
IQR : 186.1479
LB : -246.56735000000003
UB : 498.02425000000005
Number of outliers : 1548
----------------------------------
```

Insights:

- **he outliers present in our sample data can be the true outliers.**
- **It's best to remove outliers only when there is a sound reason for doing so.**
- **Some outliers represent natural variations in the population, and they should be left as is in the dataset.**

3G. Do one-hot encoding of categorical variables (like route_type):

In [131]:
```
# Get value counts before one-hot encoding
df2['route_type'].value_counts()
```

Out[131]:
```
Carting    8908
FTL        5909
Name: route_type, dtype: int64
```

Perform one-hot encoding on categorical column route type:

In [132]:
```
label_encoder = LabelEncoder()
df2['route_type'] = label_encoder.fit_transform(df2['route_type'])
```

In [133]:
```
# Get value counts after one-hot encoding
df2['route_type'].value_counts()
```

Out[133]:
```
0    8908
1    5909
Name: route_type, dtype: int64
```

In [134]:
```
# Get value counts of categorical variable 'data' before one-hot encoding
df2['data'].value_counts()
```

Out[134]:
```
training    10654
test         4163
Name: data, dtype: int64
```

Perform one-hot encoding on categorical variable 'data':

In [135]:
```
label_encoder = LabelEncoder()
df2['data'] = label_encoder.fit_transform(df2['data'])
```

In [136]:
```
# Get value counts after one-hot encoding
df2['data'].value_counts()
```

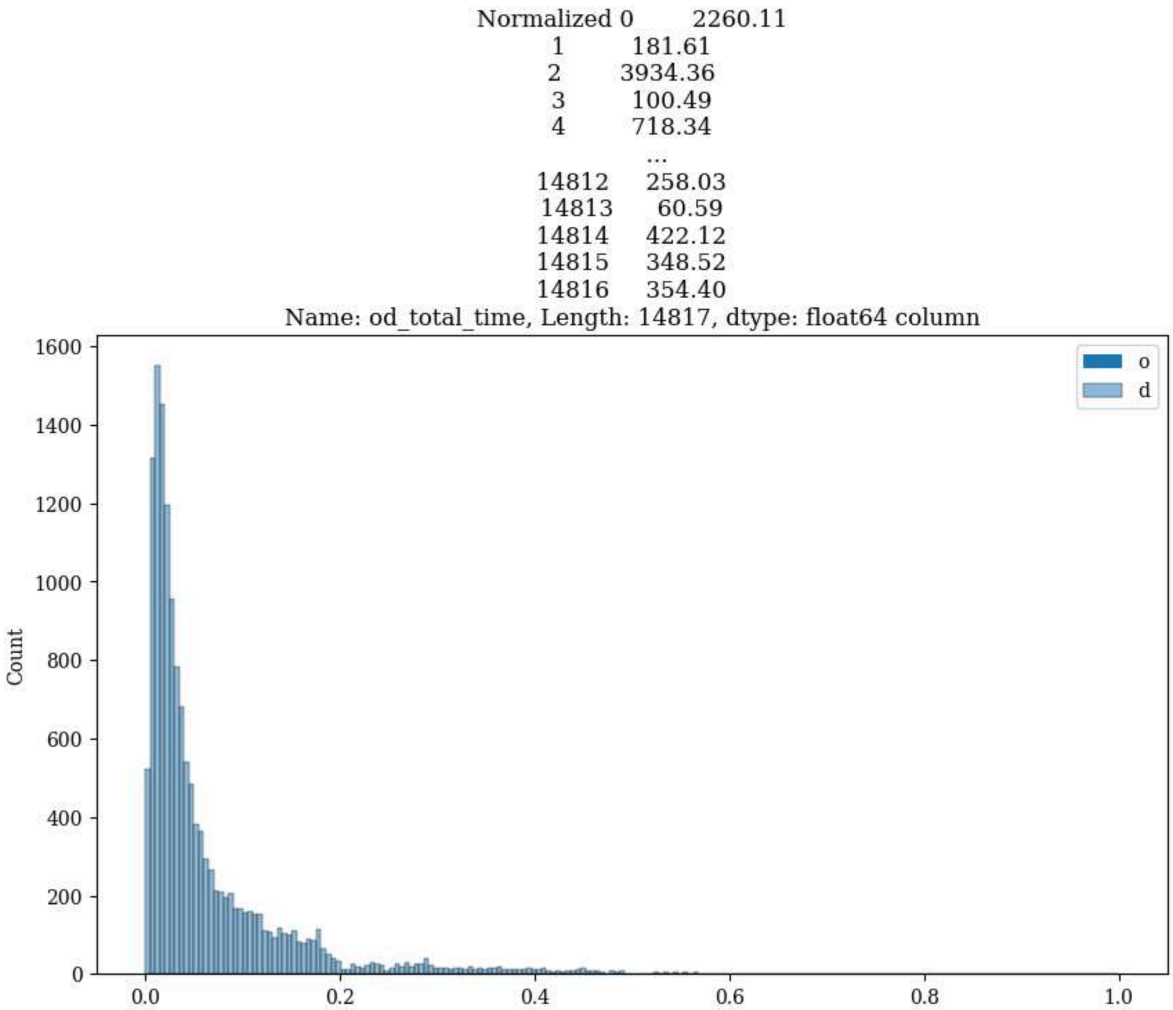
Out[136]:
```
1    10654
0     4163
Name: data, dtype: int64
```

3H. Normalize/ Standardize the numerical features using MinMaxScaler or StandardScaler:

Normalizing the numerical features:

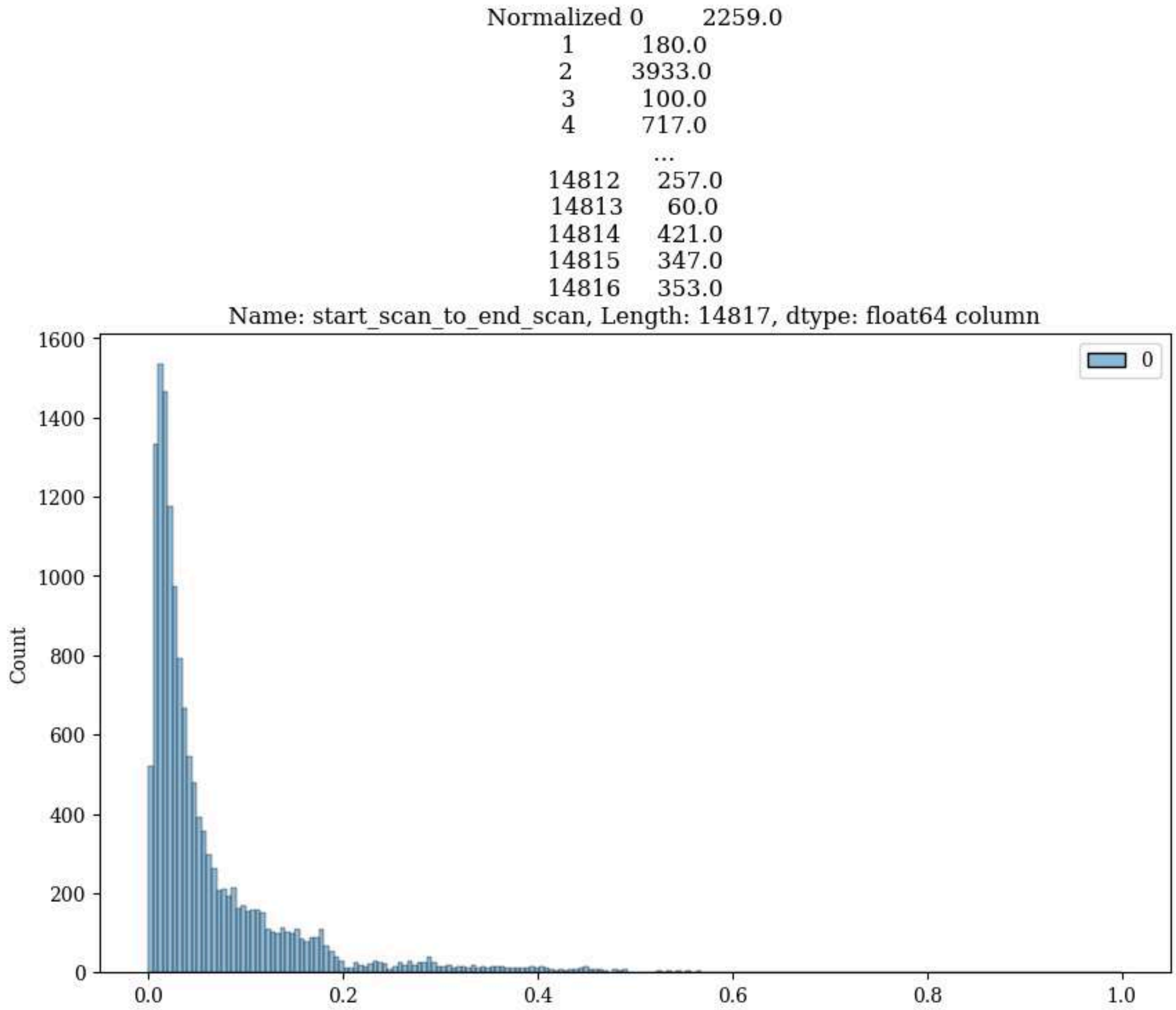
In [137]:
```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['od_total_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['od_total_time']} column")
plt.legend('od_total_time')
plt.plot()
```

Out[137]: []



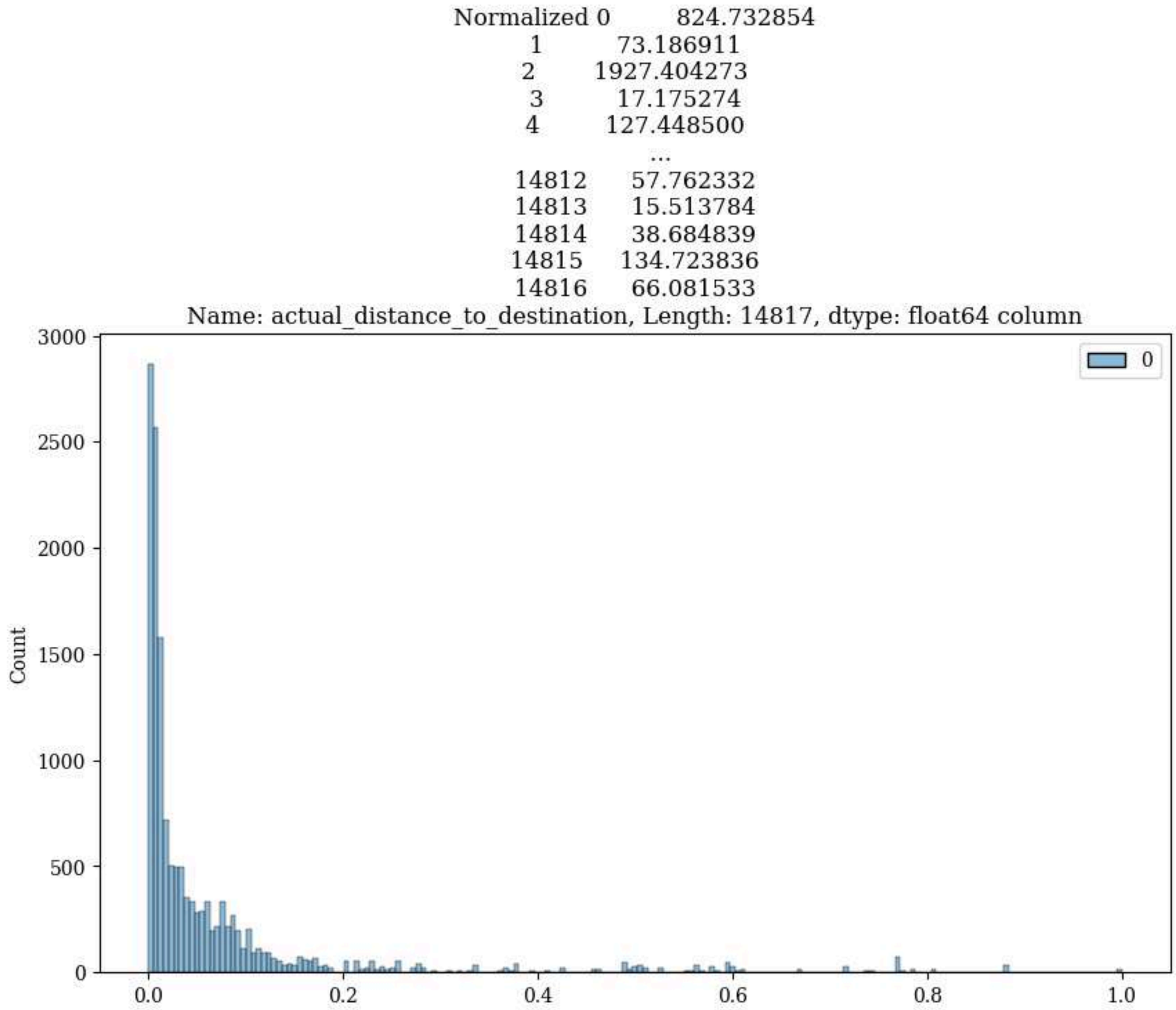
In [138]:
```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['start_scan_to_end_scan'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['start_scan_to_end_scan']} column")
plt.plot()
```

Out[138]: []



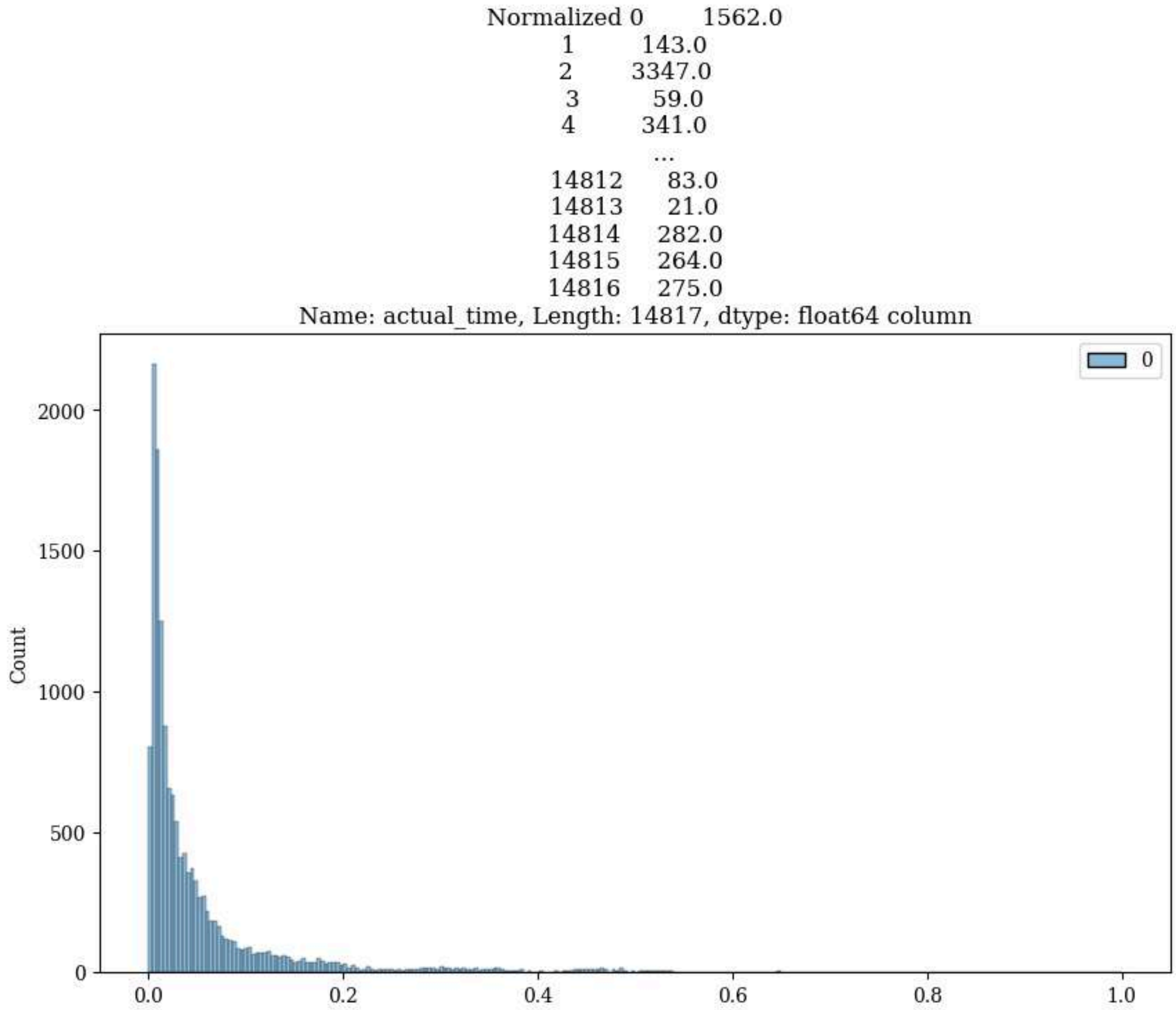
In [139]:
```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['actual_distance_to_destination'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['actual_distance_to_destination']} column")
plt.plot()
```

Out[139]: []



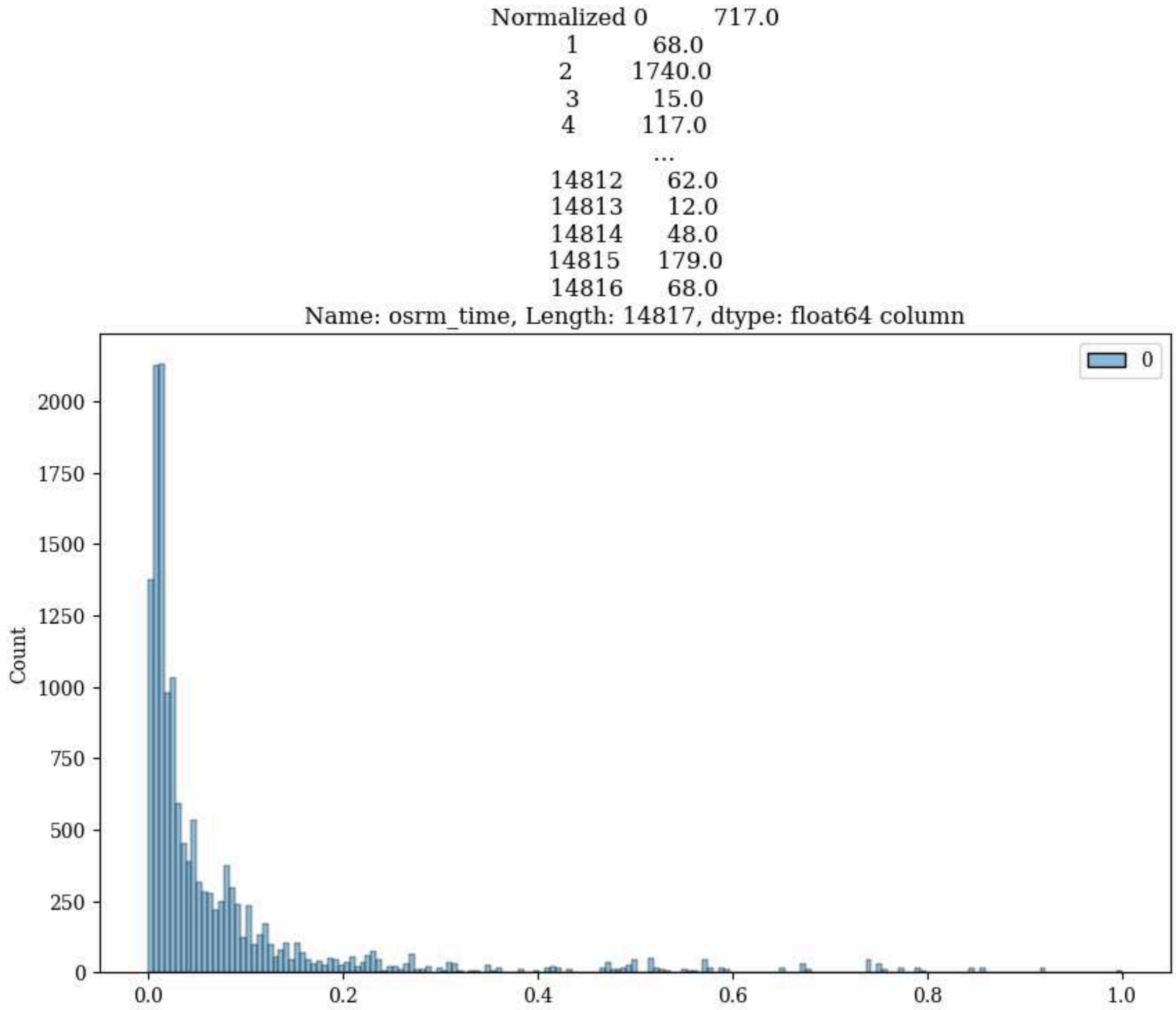
In [140]:
```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['actual_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['actual_time']} column")
plt.plot()
```

Out[140]: []



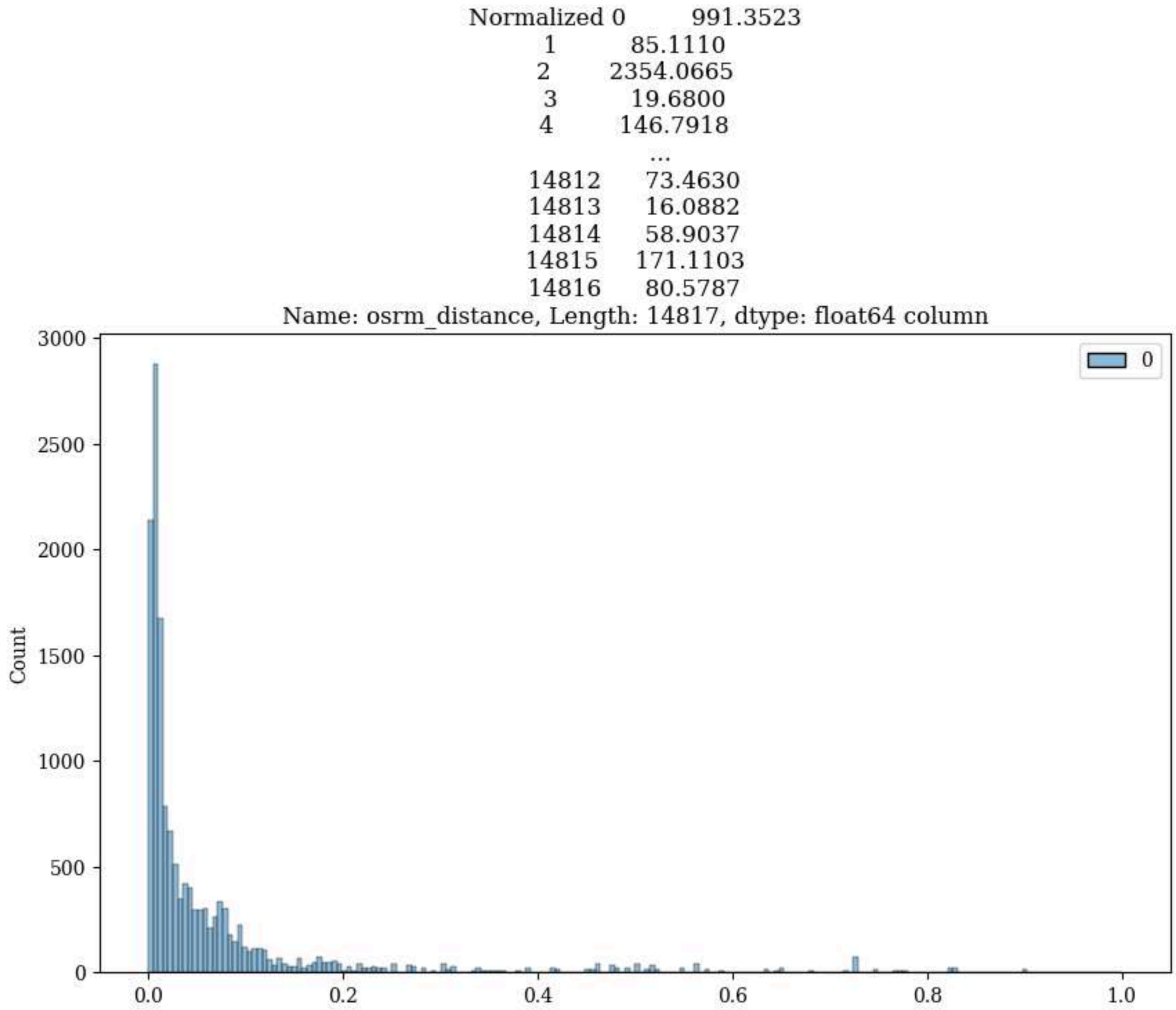
In [141]:
```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['osrm_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['osrm_time']} column")
plt.plot()
```

Out[141]: []



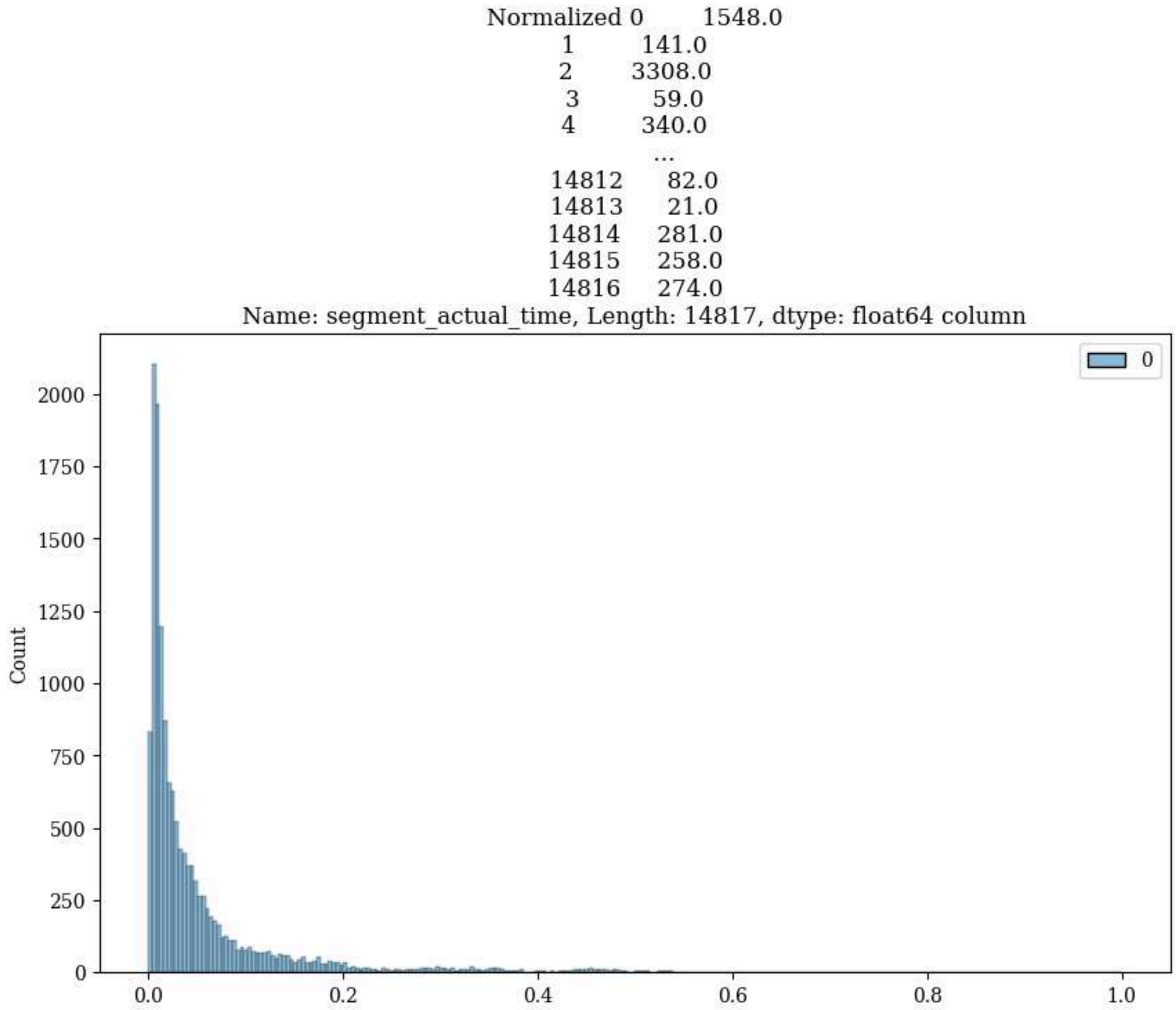
In [142]:
```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['osrm_distance'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['osrm_distance']} column")
plt.plot()
```

Out[142]: []



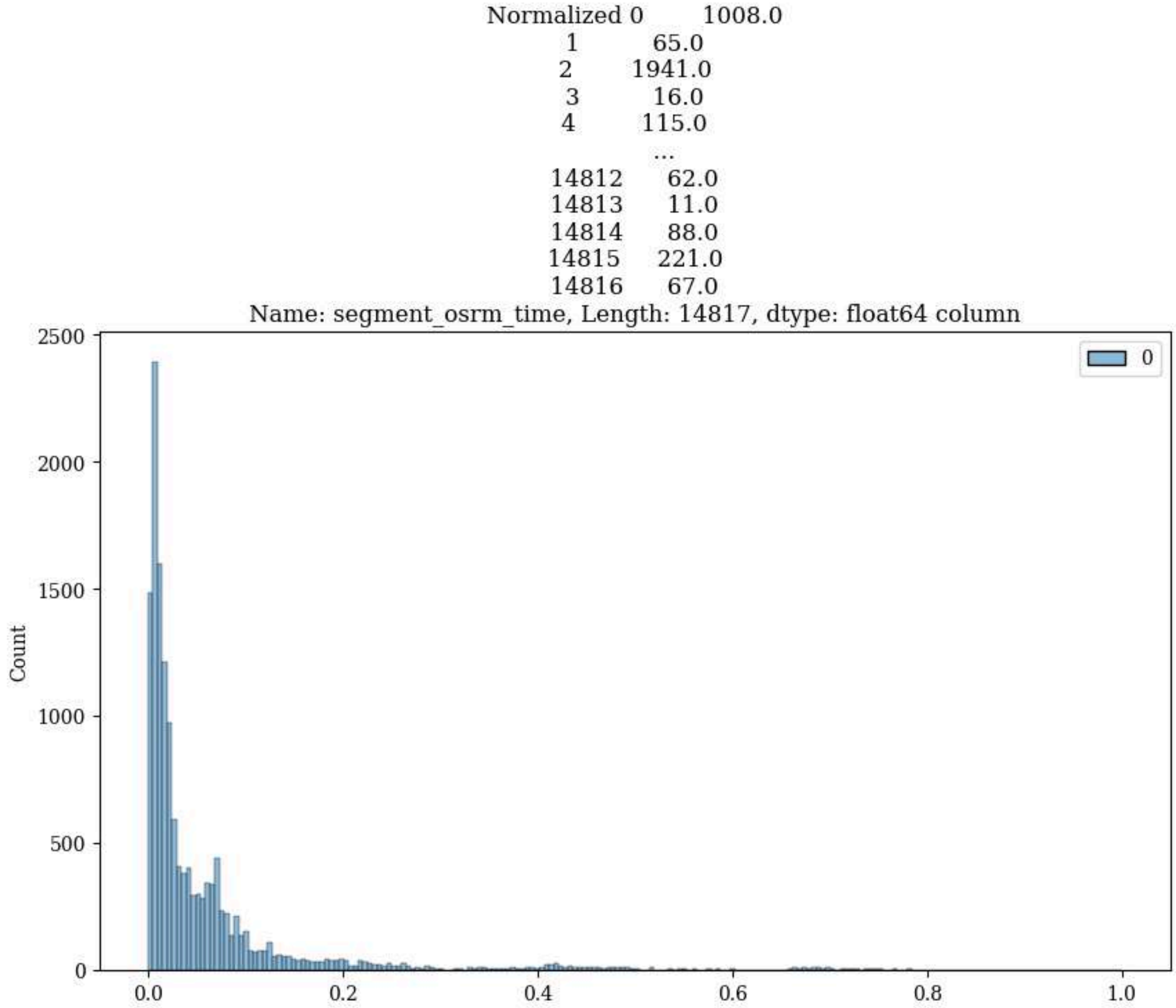
In [143]:
```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['segment_actual_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['segment_actual_time']} column")
plt.plot()
```

Out[143]: []



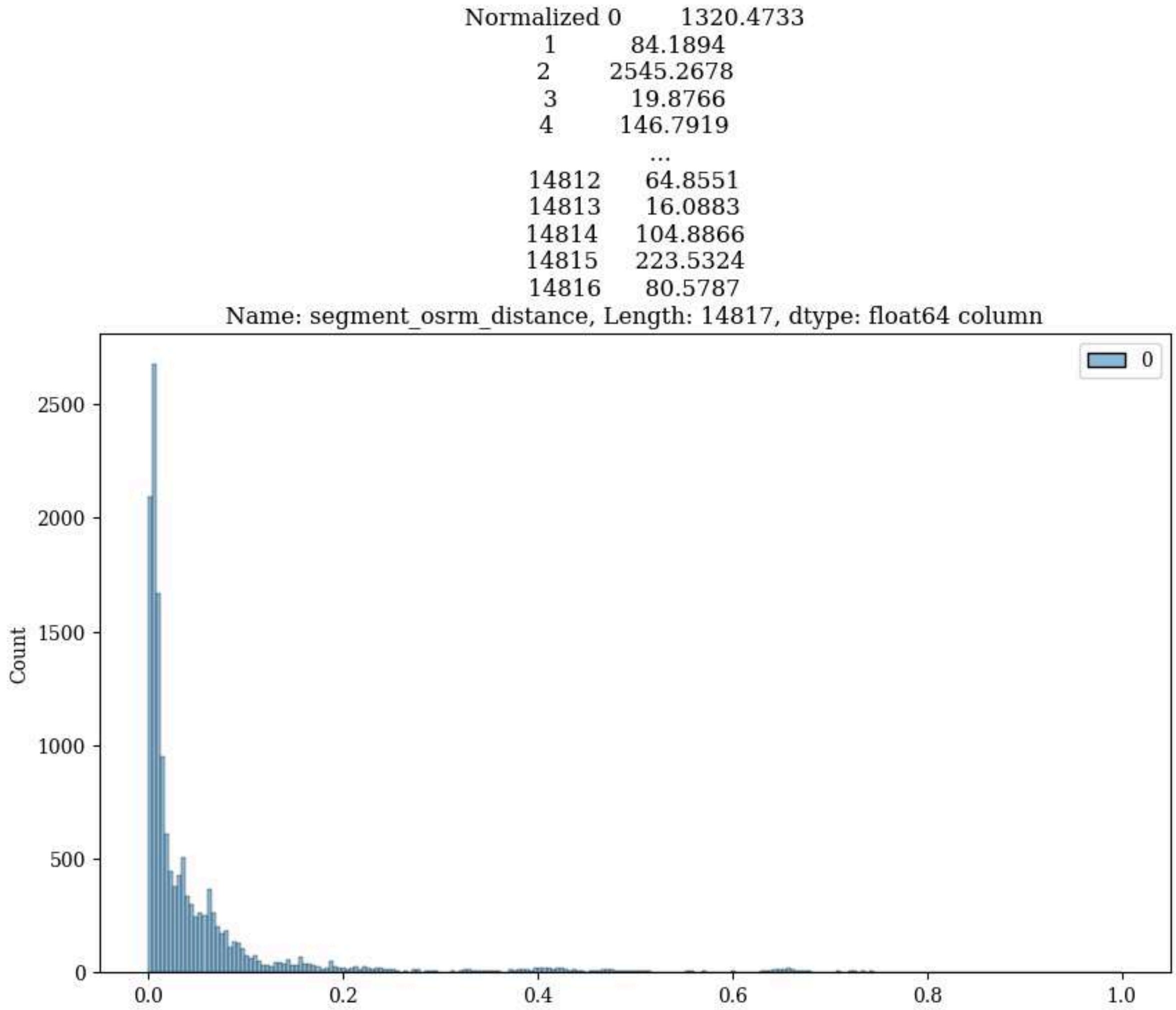
In [144]:
```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['segment_osrm_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['segment_osrm_time']} column")
plt.plot()
```

Out[144]: []



In [145]:
```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['segment_osrm_distance'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['segment_osrm_distance']} column")
plt.plot()
```

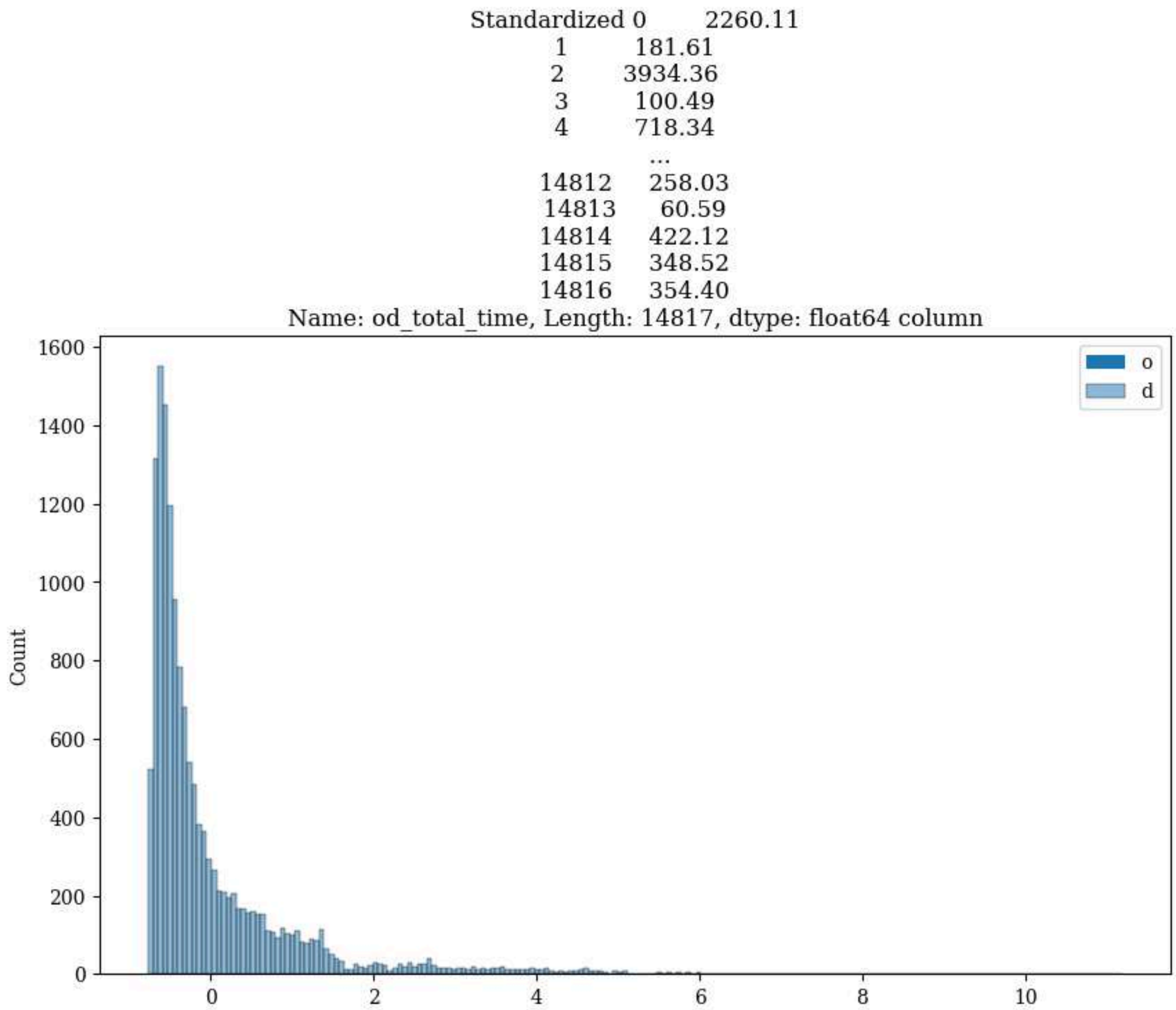
Out[145]: []



Standardizing the numerical features:

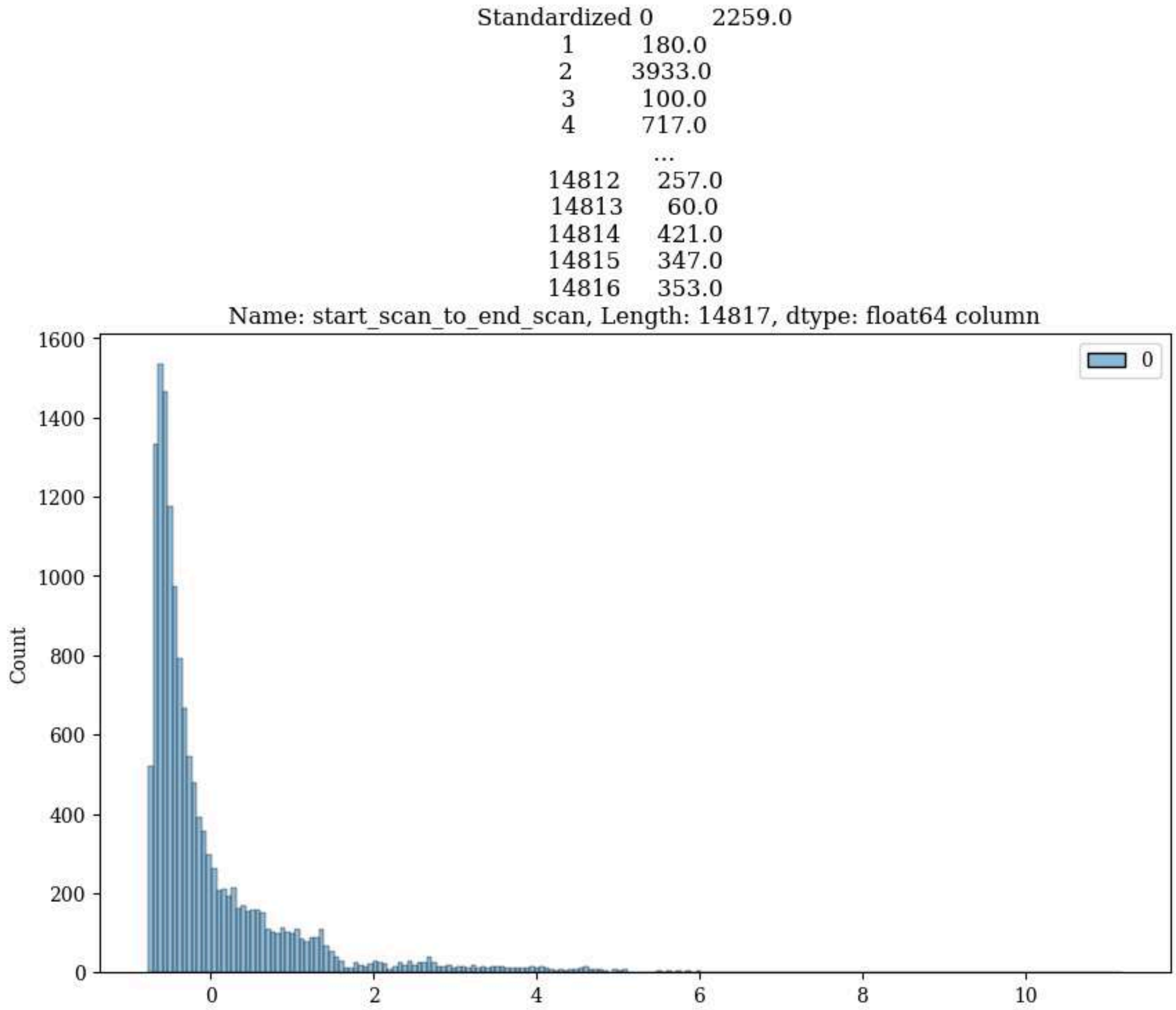
In [146]:
```
plt.figure(figsize = (10, 6))
# define standard scaler
scaler = StandardScaler()
# transform data
scaled = scaler.fit_transform(df2['od_total_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['od_total_time']} column")
plt.legend('od_total_time')
plt.plot()
```

Out[146]: []



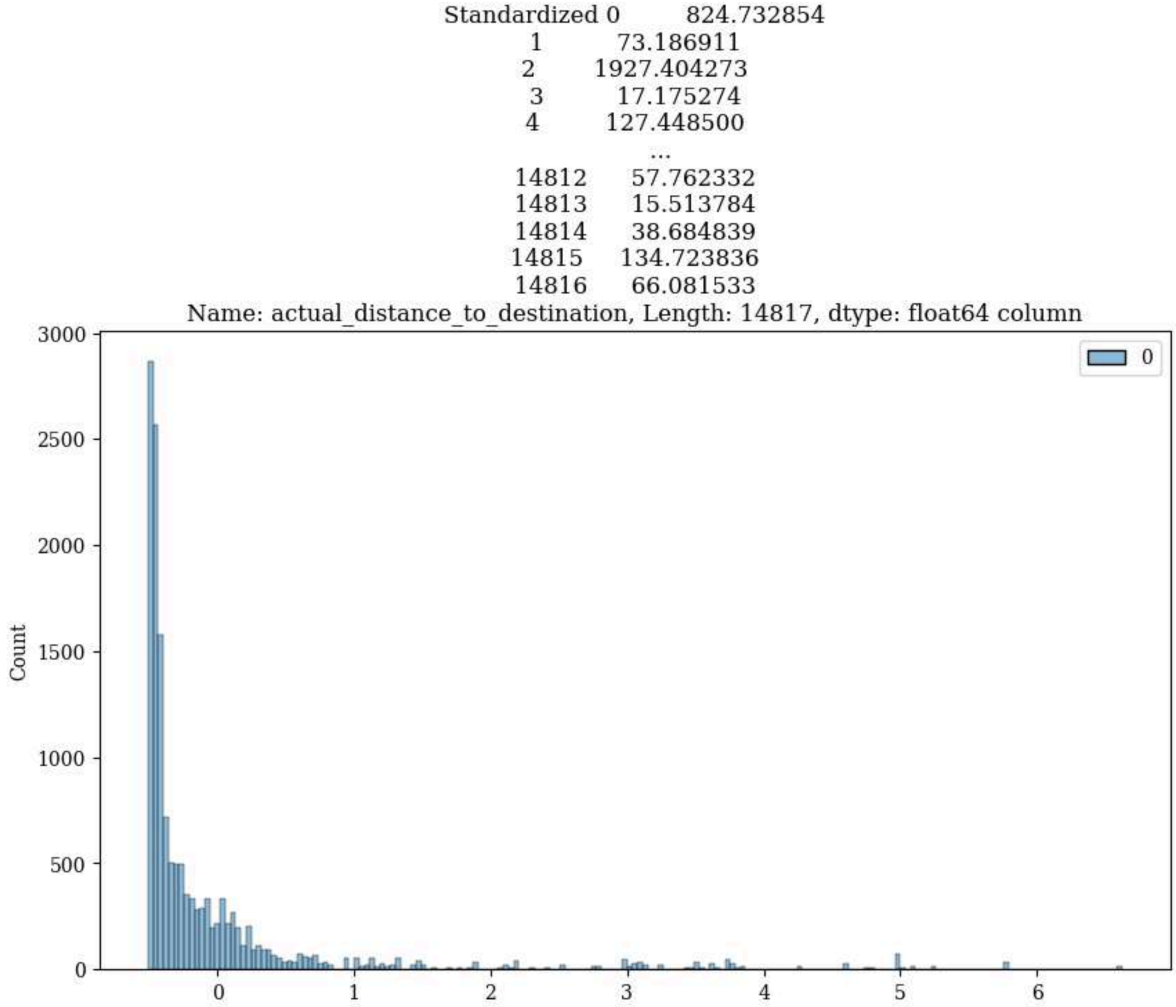
In [147]:
```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['start_scan_to_end_scan'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['start_scan_to_end_scan']} column")
plt.plot()
```

Out[147]: []



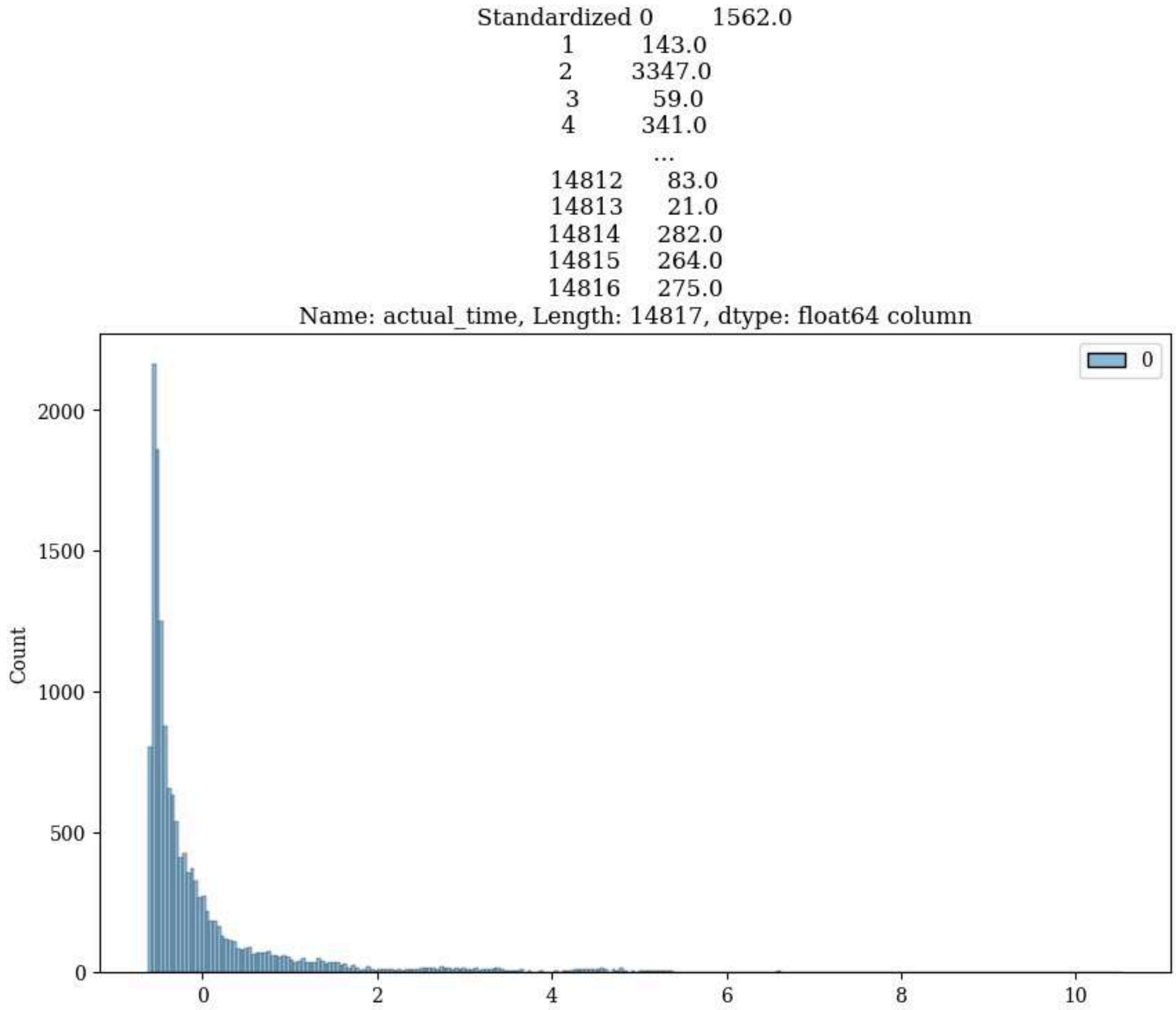
In [148]:
```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['actual_distance_to_destination'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['actual_distance_to_destination']} column")
plt.plot()
```

Out[148]: []



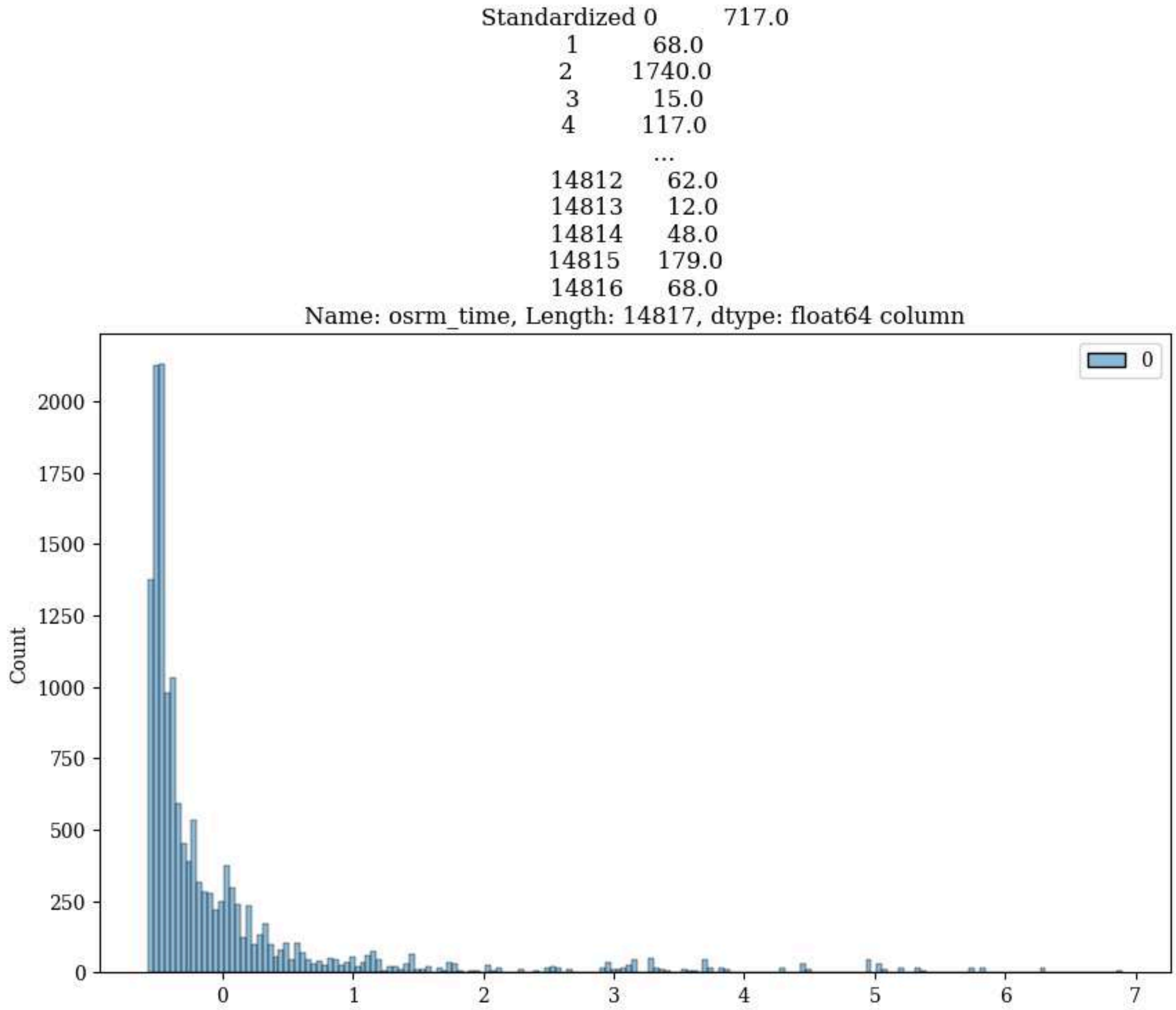
In [149]:
```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['actual_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['actual_time']} column")
plt.plot()
```

Out[149]: []



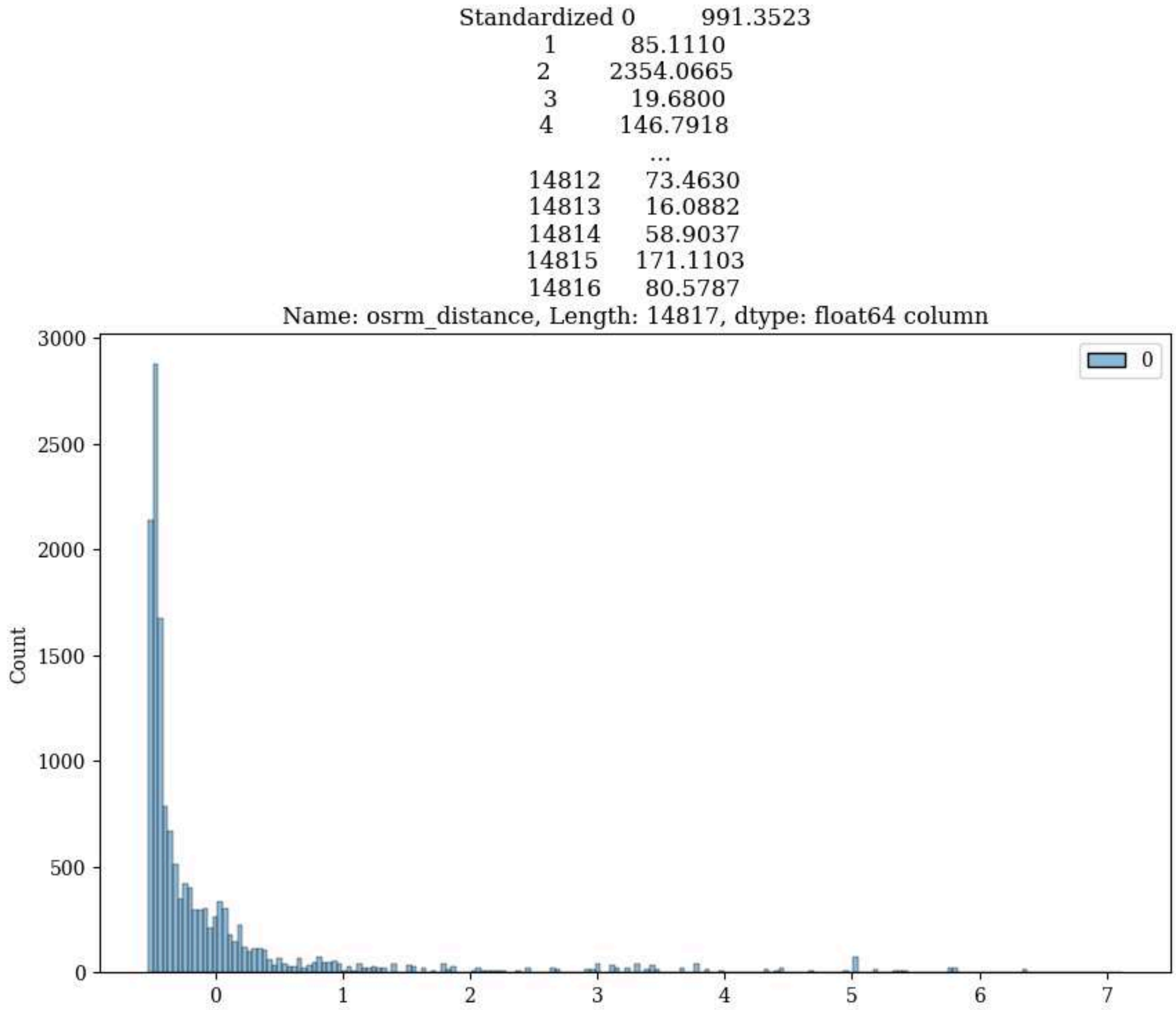
In [150]:
```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['osrm_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['osrm_time']} column")
plt.plot()
```

Out[150]: []



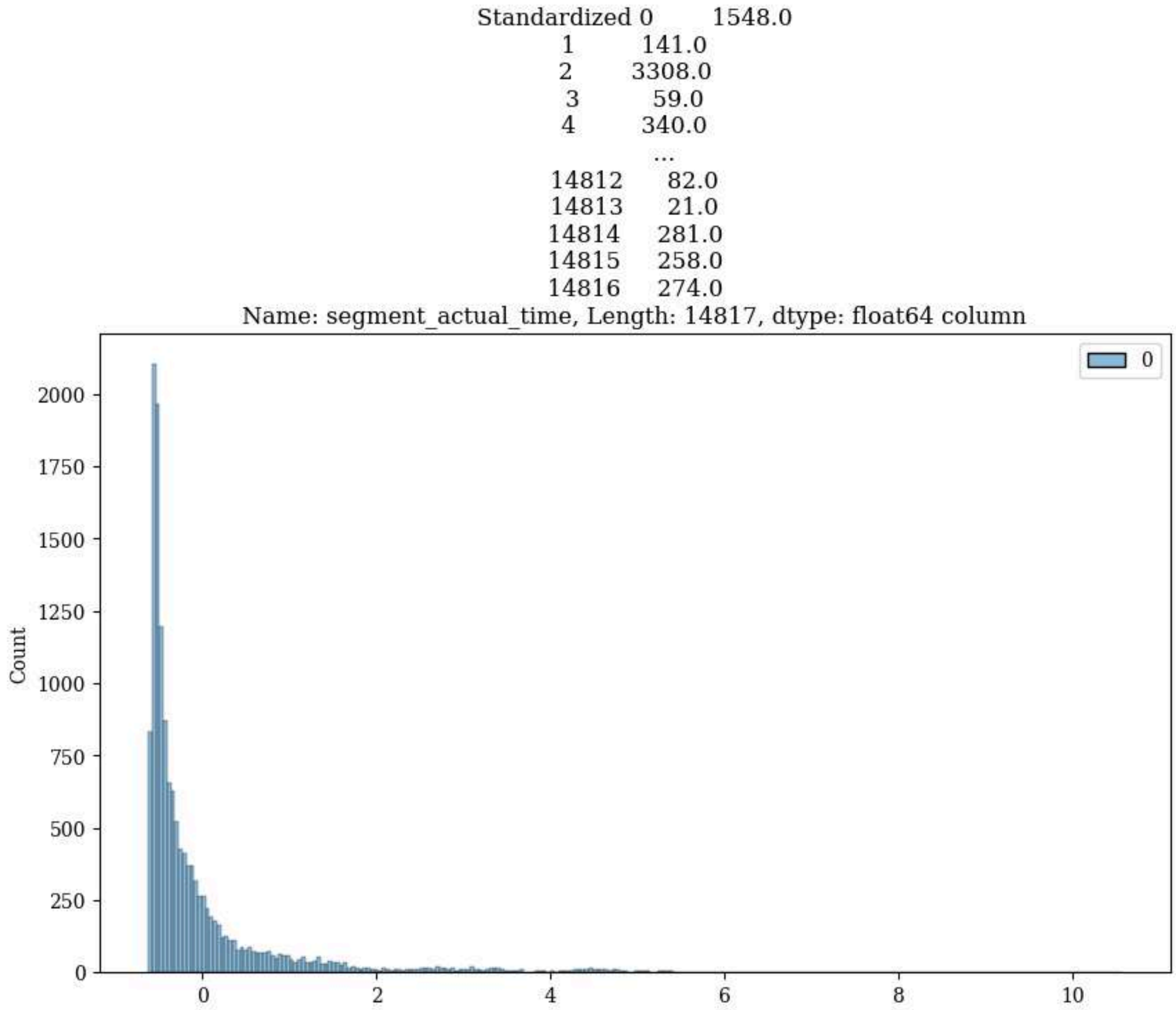
In [151]:
```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['osrm_distance'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['osrm_distance']} column")
plt.plot()
```

Out[151]: []



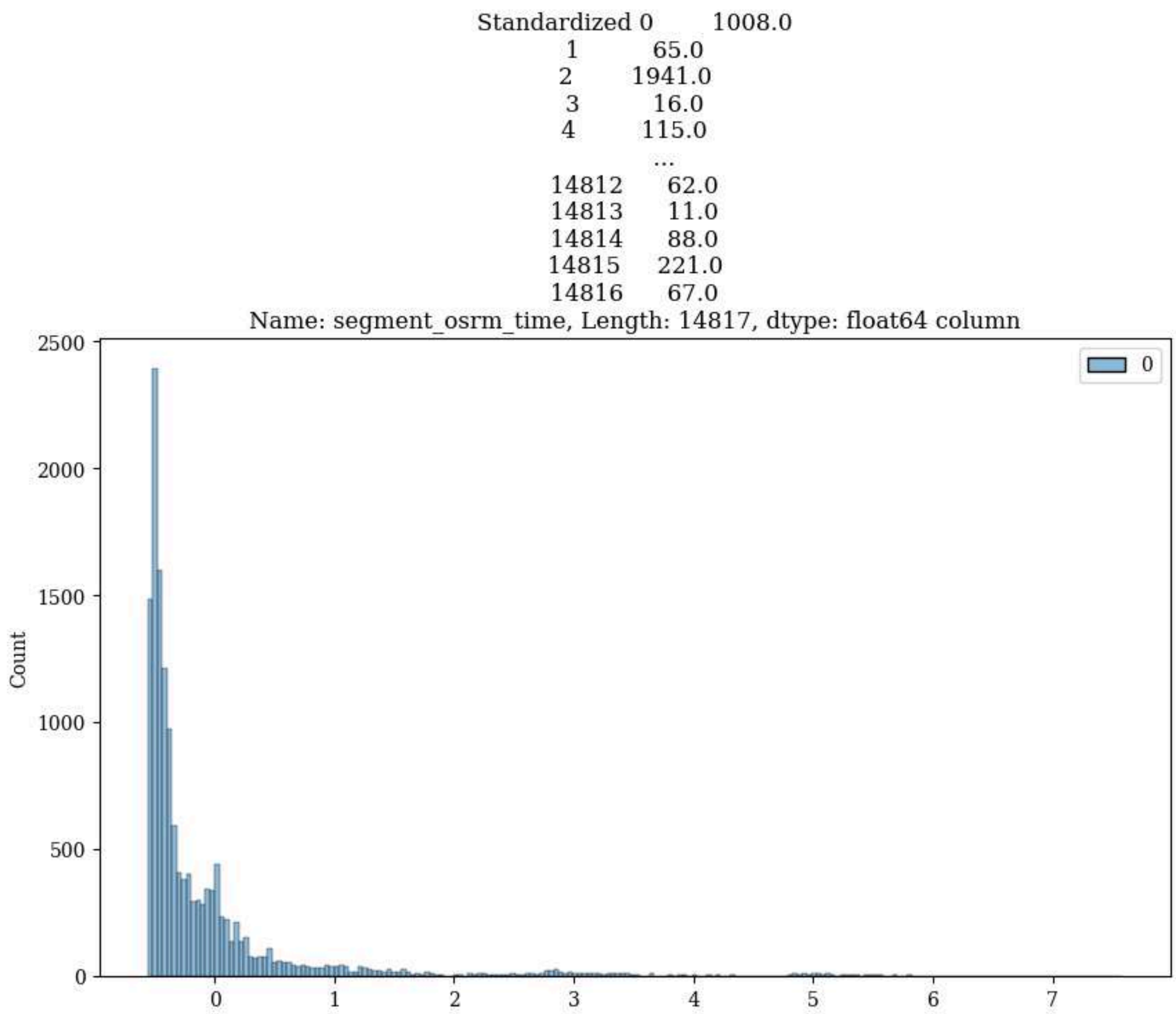
In [152]:
```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['segment_actual_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['segment_actual_time']} column")
plt.plot()
```

Out[152]: []



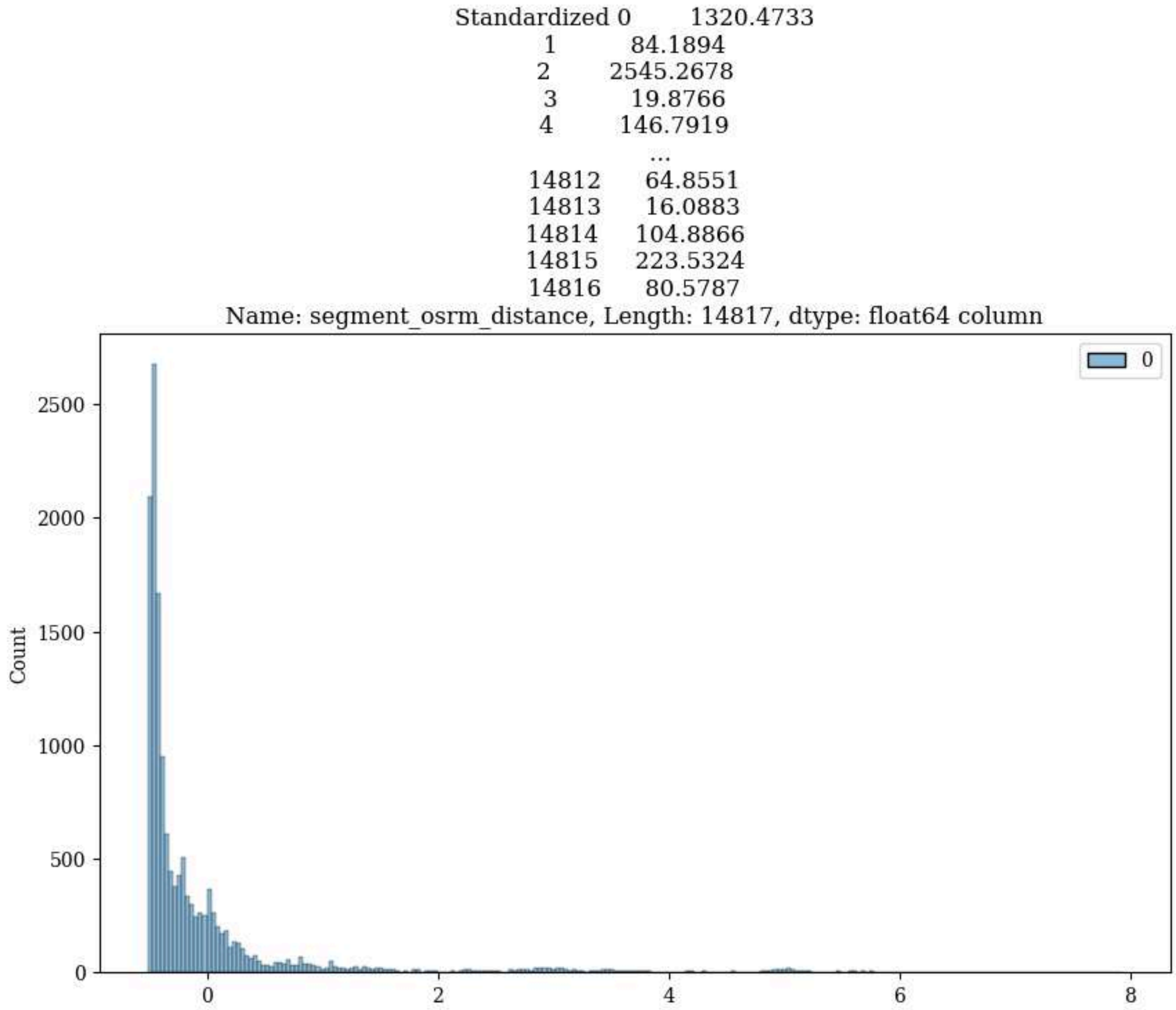
In [153]:
```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['segment_osrm_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['segment_osrm_time']} column")
plt.plot()
```

Out[153]: []



In [154]:
```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['segment_osrm_distance'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['segment_osrm_distance']} column")
plt.plot()
```

Out[154]: []



Insights:

- The data is given from the period '2018-09-12 00:00:16' to '2018-10-08 03:00:24'.
- There are about 14817 unique trip IDs, 1508 unique source centers, 1481 unique destination_centers, 690 unique source cities, 806 unique destination cities.
- Most of the data is for testing than for training.
- Most common route type is Carting.
- The names of 14 unique location ids are missing in the data.
- The number of trips start increasing after the noon, becomes maximum at 10 P.M and then start decreasing.
- Maximum trips are created in the 38th week.
- Most orders come mid-month. That means customers usually make more orders in the mid of the month.
- Most orders are sourced from the states like Maharashtra, Karnataka, Haryana, Tamil Nadu, Telangana
- Maximum number of trips originated from Mumbai city followed by Gurgaon Delhi, Bengaluru and Bhiwandi. That means that the seller base is strong in these cities.
- Maximum number of trips ended in Maharashtra state followed by Karnataka, Haryana, Tamil Nadu and Uttar Pradesh. That means that the number of orders placed in these states is significantly high.
- Maximum number of trips ended in Mumbai city followed by Bengaluru, Gurgaon, Delhi and Chennai. That means that the number of orders placed in these cities is significantly high.
- Most orders in terms of destination are coming from cities like bengaluru, mumbai, gurgaon, bangalore, Delhi.
- Features start_scan_to_end_scan and od_total_time(created feature) are statistically similar.
- Features actual_time & osrm_time are statitically different.
- Features start_scan_to_end_scan and segment_actual_time are statistically similar.
- Features osrm_distance and segment_osrm_distance are statistically different from each other.
- Both the osrm_time & segment_osrm_time are not statistically same.

Business 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.