Business Case: Delhivery - Feature Engineering

About Delhivery

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

How can you help here?

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

• Clean, sanitize and manipulate data to get useful features out of raw fields

• Make sense out of the raw data and help the data science team to build forecasting models on it

Importing Required Libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib as mpl
import matplotlib.pyplot as plt
import scipy.stats as spy
```

In [2]:
```
import warnings
warnings.simplefilter('ignore')
```

Loading the Dataset

In [3]:
```
df = pd.read_csv(r"https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/551/original/delhivery_data.c
```

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

Out[4]:

	data	trip_creation_time	route_schedule_uuid	route_type	trip_uuid	source_center	source_name	destination_center
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
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
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
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
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

5 rows × 24 columns

What is the shape of the loaded dataset ?

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

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

What are the columns present in the dataset?

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

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

What is the datatype of the columns ?

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

Out[7]:
```
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 [8]:
```
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
```

Dropping unknown fields

In [9]:
```
unknown_fields = ['is_cutoff', 'cutoff_factor', 'cutoff_timestamp', 'factor', 'segment_factor']
df = df.drop(columns = unknown_fields)
```

How many unique entries present in each column ?

In [10]:
```
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 [11]:
```
df['data'] = df['data'].astype('category')
df['route_type'] = df['route_type'].astype('category')
```

In [12]:
```
floating_columns = ['actual_distance_to_destination', 'actual_time', 'osrm_time', 'osrm_distance',
                    'segment_actual_time', 'segment_osrm_time', 'segment_osrm_distance']
for i in floating_columns:
    print(df[i].max())
```

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

We can update the datatype to float32 since the maximum value entry is small

In [13]:
```
for i in floating_columns:
    df[i] = df[i].astype('float32')
```

Updating the datatype of the datetime columns

In [14]:
```
datetime_columns = ['trip_creation_time', 'od_start_time', 'od_end_time']
for i in datetime_columns:
    df[i] = pd.to_datetime(df[i])
```

In [15]:
```
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  float32
 13  actual_time                     144867 non-null  float32
 14  osrm_time                       144867 non-null  float32
 15  osrm_distance                   144867 non-null  float32
 16  segment_actual_time             144867 non-null  float32
 17  segment_osrm_time               144867 non-null  float32
 18  segment_osrm_distance           144867 non-null  float32
dtypes: category(2), datetime64[ns](3), float32(7), float64(1), object(6)
memory usage: 15.2+ MB
```

Earlier the dataset was using 25.6+ MB of memory but now it has been reduced to 15.2 + MB. Around 40.63 % reduction in the memory usage.

What is the time period for which the data is given ?

In [16]:
```
df['trip_creation_time'].min(), df['od_end_time'].max()
```

Out[16]:
```
(Timestamp('2018-09-12 00:00:16.535741'),
 Timestamp('2018-10-08 03:00:24.353479'))
```

1. Basic data cleaning and exploration:

Handling missing values in the data

Is there any null values present in the dataset ?

In [17]:
```
np.any(df.isnull())
```

Out[17]:
```
True
```

What is the number of null values present in each column ?

In [18]:
```
df.isnull().sum()
```

Out[18]:
```
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 [19]:
```
missing_source_name = df.loc[df['source_name'].isnull(), 'source_center'].unique()
missing_source_name
```

Out[19]:
```
array(['IND342902A1B', 'IND577116AAA', 'IND282002AAD', 'IND465333A1B',
       'IND841301AAC', 'IND509103AAC', 'IND126116AAA', 'IND331022A1B',
       'IND505326AAB', 'IND852118A1B'], dtype=object)
```

In [20]:
```
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 [21]:
```
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
```

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)
```

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

In [23]:
```
np.all(df.loc[df['source_name'].isnull(), 'source_center'].isin(missing_destination_name))
```

Out[23]:
```
False
```

Treating missing destination names and source names

In [24]:
```
count = 1
for i in missing_destination_name:
    df.loc[df['destination_center'] == i, 'destination_name'] = df.loc[df['destination_center'] == i, 'destination_
    count += 1
```

In [25]:
```
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 [26]:
```
for i in missing_source_name:
    df.loc[df['source_center'] == i, 'source_name'] = df.loc[df['source_center'] == i, 'source_name'].replace(np.na
```

In [27]:
```
df.isna().sum()
```

Out[27]:
```
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
```

Basic Description of the Data

In [28]:
```
df.describe()
```

Out[28]:

	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	segment_actual_time	segment_os
count	144867.000000	144867.000000	144867.000000	144867.000000	144867.000000	144867.000000	14486
mean	961.262986	234.050812	416.929504	213.864685	284.768158	36.196110	1
std	1037.012769	344.979126	598.096069	308.004333	421.117462	53.566002	1
min	20.000000	9.000046	9.000000	6.000000	9.008200	-244.000000	
25%	161.000000	23.355875	51.000000	27.000000	29.914701	20.000000	1
50%	449.000000	66.126572	132.000000	64.000000	78.525803	29.000000	1
75%	1634.000000	286.708878	513.000000	257.000000	343.193253	40.000000	2
max	7898.000000	1927.447754	4532.000000	1686.000000	2326.199219	3051.000000	161

In [29]:
```
df.describe(include = 'object')
```

Out[29]:

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

Merging of rows and aggregation of fields

How to begin"

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

In [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	destinat
0	trip-153671041653548748	IND209304AAA	IND000000ACB	training	FTL	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	Gurgaon_Bi
1	trip-153671041653548748	IND462022AAA	IND209304AAA	training	FTL	2018-09-12 00:00:16.535741	Bhopal_Trnsport_H (Madhya Pradesh)	Kanpur_Central_
2	trip-153671042288605164	IND561203AAB	IND562101AAA	training	Carting	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	Chikblapur_S (I
3	trip-153671042288605164	IND572101AAA	IND561203AAB	training	Carting	2018-09-12 00:00:22.886430	Tumkur_Veersagr_I (Karnataka)	Doddablpur_Ch (I
4	trip-153671043369099517	IND000000ACB	IND160002AAC	training	FTL	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)	Chandigarh_Me
...	...	...	...	...	...	...	...	
26363	trip-153861115439069069	IND628204AAA	IND627657AAA	test	Carting	2018-10-03 23:59:14.390954	Tirchchndr_Shnmgprm_D (Tamil Nadu)	Thisayanvilai_Ud (Ta
26364	trip-153861115439069069	IND628613AAA	IND627005AAA	test	Carting	2018-10-03 23:59:14.390954	Peikulam_SriVnktpm_D (Tamil Nadu)	Tirunelveli_\ (Ta
26365	trip-153861115439069069	IND628801AAA	IND628204AAA	test	Carting	2018-10-03 23:59:14.390954	Eral_Busstand_D (Tamil Nadu)	Tirchchndr_Shr (Ta
26366	trip-153861118270144424	IND583119AAA	IND583101AAA	test	FTL	2018-10-03 23:59:42.701692	Sandur_WrdN1DPP_D (Karnataka)	Bellary_Dc (I
26367	trip-153861118270144424	IND583201AAA	IND583119AAA	test	FTL	2018-10-03 23:59:42.701692	Hospet (Karnataka)	Sandur_Wrd (I

26368 rows × 18 columns

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

In [31]:
```python
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]:
```python
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	destinati
0	trip-153671041653548748	IND209304AAA	IND209304AAA	training	FTL	2018-09-12 00:00:16.535741	Kanpur_Central_H_6 (Uttar Pradesh)	Kanpur_Ce (Uttar
1	trip-153671042288605164	IND561203AAB	IND561203AAB	training	Carting	2018-09-12 00:00:22.886430	Doddablpur_ChikaDPP_D (Karnataka)	Doddablpur_Chi (K
2	trip-153671043369099517	IND000000ACB	IND000000ACB	training	FTL	2018-09-12 00:00:33.691250	Gurgaon_Bilaspur_HB (Haryana)	Gurgaon_Bil
3	trip-153671046011330457	IND400072AAB	IND401104AAA	training	Carting	2018-09-12 00:01:00.113710	Mumbai Hub (Maharashtra)	Mumbai_I (Mal
4	trip-153671052974046625	IND583101AAA	IND583119AAA	training	FTL	2018-09-12 00:02:09.740725	Bellary_Dc (Karnataka)	Sandur_Wrdl (K
...	...	...	...	...	...	...	...	...
14812	trip-153861095625827784	IND160002AAC	IND160002AAC	test	Carting	2018-10-03 23:55:56.258533	Chandigarh_Mehmdpur_H (Punjab)	Chandigarh_Mel
14813	trip-153861104386292051	IND121004AAB	IND121004AAA	test	Carting	2018-10-03 23:57:23.863155	FBD_Balabhgarh_DPC (Haryana)	Faridabad_Bl
14814	trip-153861106442901555	IND208006AAA	IND208006AAA	test	Carting	2018-10-03 23:57:44.429324	Kanpur_GovndNgr_DC (Uttar Pradesh)	Kanpur_Govr (Uttar
14815	trip-153861115439069069	IND627005AAA	IND628204AAA	test	Carting	2018-10-03 23:59:14.390954	Tirunelveli_VdkkuSrt_I (Tamil Nadu)	Tirchchndr_Shn (Ta
14816	trip-153861118270144424	IND583119AAA	IND583119AAA	test	FTL	2018-10-03 23:59:42.701692	Sandur_WrdN1DPP_D (Karnataka)	Sandur_Wrdl (K

14817 rows × 17 columns

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

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

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

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

In [35]:
```python
def location_name_to_place(x):
    if 'location' in x:
        return x
    elif 'HBR' in x:
        return 'HBR Layout PC'
    else:
        l = x.split()[0].split('_', 1)
        if len(l) == 1:
            return 'unknown_place'
        else:
            return l[1]
```

In [36]:
```python
df2['source_state'] = df2['source_name'].apply(location_name_to_state)
df2['source_state'].unique()
```

Out[36]:
```
array(['Uttar Pradesh', 'Karnataka', 'Haryana', 'Maharashtra',
       'Tamil Nadu', 'Gujarat', 'Delhi', 'Telangana', 'Rajasthan',
       'Assam', 'Madhya Pradesh', 'West Bengal', 'Andhra Pradesh',
       'Punjab', 'Chandigarh', 'Goa', 'Jharkhand', 'Pondicherry',
       'Orissa', 'Uttarakhand', 'Himachal Pradesh', 'Kerala',
       'Arunachal Pradesh', 'Bihar', 'Chhattisgarh',
       'Dadra and Nagar Haveli', 'Jammu & Kashmir', 'Mizoram', 'Nagaland',
       'location_9', 'location_3', 'location_2', 'location_14',
       'location_7'], dtype=object)
```

In [37]:
```python
df2['source_city'] = df2['source_name'].apply(location_name_to_city)
print('No of source cities :', df2['source_city'].nunique())
df2['source_city'].unique()[:100]
```

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

Out[37]:
```
array(['Kanpur', 'Doddablpur', 'Gurgaon', 'Mumbai', 'Bellary', 'Chennai',
       'Bengaluru', 'Surat', 'Delhi', 'Pune', 'Faridabad', 'Shirala',
       'Hyderabad', 'Thirumalagiri', 'Gulbarga', 'Jaipur', 'Allahabad',
       'Guwahati', 'Narsinghpur', 'Shrirampur', 'Madakasira', 'Sonari',
       'Dindigul', 'Jalandhar', 'Chandigarh', 'Deoli', 'Pandharpur',
       'Kolkata', 'Bhandara', 'Kurnool', 'Bhiwandi', 'Bhatinda',
       'RoopNagar', 'Bantwal', 'Lalru', 'Kadi', 'Shahdol', 'Gangakher',
       'Durgapur', 'Vapi', 'Jamjodhpur', 'Jetpur', 'Mehsana', 'Jabalpur',
       'Junagadh', 'Gundlupet', 'Mysore', 'Goa', 'Bhopal', 'Sonipat',
       'Himmatnagar', 'Jamshedpur', 'Pondicherry', 'Anand', 'Udgir',
       'Nadiad', 'Villupuram', 'Purulia', 'Bhubaneshwar', 'Bamangola',
       'Tiruppattur', 'Kotdwara', 'Medak', 'Bangalore', 'Dhrangadhra',
       'Hospet', 'Ghumarwin', 'Agra', 'Sitapur', 'Canacona', 'Bilimora',
       'SultnBthry', 'Lucknow', 'Vellore', 'Bhuj', 'Dinhata',
       'Margherita', 'Boisar', 'Vizag', 'Tezpur', 'Koduru', 'Tirupati',
       'Pen', 'Ahmedabad', 'Faizabad', 'Gandhinagar', 'Anantapur',
       'Betul', 'Panskura', 'Rasipurm', 'Sankari', 'Jorhat', 'PNQ',
       'Srikakulam', 'Dehradun', 'Jassur', 'Sawantwadi', 'Shajapur',
       'Ludhiana', 'GreaterThane'], dtype=object)
```

In [38]:
```
df2['source_place'] = df2['source_name'].apply(location_name_to_place)
df2['source_place'].unique()[:100]
```

Out[38]:
```
array(['Central_H_6', 'ChikaDPP_D', 'Bilaspur_HB', 'unknown_place', 'Dc',
       'Poonamallee', 'Chrompet_DPC', 'HBR Layout PC', 'Central_D_12',
       'Lajpat_IP', 'North_D_3', 'Balabhgarh_DPC', 'Central_DPP_3',
       'Shamshbd_H', 'Xroad_D', 'Nehrugnj_I', 'Central_I_7',
       'Central_H_1', 'Nangli_IP', 'North', 'KndliDPP_D', 'Central_D_9',
       'DavkharRd_D', 'Bandel_D', 'RTCStand_D', 'Central_DPP_1',
       'KGAirprt_HB', 'North_D_2', 'Central_D_1', 'DC', 'Mthurard_L',
       'Mullanpr_DC', 'Central_DPP_2', 'RajCmplx_D', 'Beliaghata_DPC',
       'RjnaiDPP_D', 'AbbasNgr_I', 'Mankoli_HB', 'DPC', 'Airport_H',
       'Hub', 'Gateway_HB', 'Tathawde_H', 'ChotiHvl_DC', 'Trmltmpl_D',
       'OnkarDPP_D', 'Mehmdpur_H', 'KaranNGR_D', 'Sohagpur_D',
       'Chrompet_L', 'Busstand_D', 'Central_I_1', 'IndEstat_I', 'Court_D',
       'Panchot_IP', 'Adhartal_IP', 'DumDum_DPC', 'Bomsndra_HB',
       'Swamylyt_D', 'Yadvgiri_IP', 'Old', 'Kundli_H', 'Central_I_3',
       'Vasanthm_I', 'Poonamallee_HB', 'VUNagar_DC', 'NlgaonRd_D',
       'Bnnrghta_L', 'Thirumtr_IP', 'GariDPP_D', 'Jogshwri_I',
       'KoilStrt_D', 'CotnGren_M', 'Nzbadrd_D', 'Dwaraka_D', 'Nelmngla_H',
       'NvygRDPP_D', 'Gndhichk_D', 'Central_D_3', 'Chowk_D', 'CharRsta_D',
       'Kollgpra_D', 'Peenya_IP', 'GndhiNgr_IP', 'Sanpada_I',
       'WrdN4DPP_D', 'Sakinaka_RP', 'CivilHPL_D', 'OstwlEmp_D',
       'Gajuwaka', 'Mhbhirab_D', 'MGRoad_D', 'Balajicly_I', 'BljiMrkt_D',
       'Dankuni_HB', 'Trnsport_H', 'Rakhial', 'Memnagar', 'East_I_21',
       'Mithakal_D'], dtype=object)
```

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

In [39]:
```
df2['destination_state'] = df2['destination_name'].apply(location_name_to_state)
df2['destination_state'].head(10)
```

Out[39]:
```
0    Uttar Pradesh
1        Karnataka
2          Haryana
3      Maharashtra
4        Karnataka
5       Tamil Nadu
6       Tamil Nadu
7        Karnataka
8          Gujarat
9            Delhi
Name: destination_state, dtype: object
```

In [40]:
```
df2['destination_city'] = df2['destination_name'].apply(location_name_to_city)
df2['destination_city'].head()
```

Out[40]:
```
0        Kanpur
1    Doddablpur
2       Gurgaon
3        Mumbai
4        Sandur
Name: destination_city, dtype: object
```

In [41]:
```
df2['destination_place'] = df2['destination_name'].apply(location_name_to_place)
df2['destination_place'].head()
```

Out[41]:
```
0    Central_H_6
1     ChikaDPP_D
2    Bilaspur_HB
3      MiraRd_IP
4     WrdN1DPP_D
Name: destination_place, dtype: object
```

Trip_creation_time: Extract features like month, year and day etc

In [42]:
```
df2['trip_creation_date'] = pd.to_datetime(df2['trip_creation_time'].dt.date)
df2['trip_creation_date'].head()
```

Out[42]:
```
0   2018-09-12
1   2018-09-12
2   2018-09-12
3   2018-09-12
4   2018-09-12
Name: trip_creation_date, dtype: datetime64[ns]
```

In [43]:
```
df2['trip_creation_day'] = df2['trip_creation_time'].dt.day
df2['trip_creation_day'] = df2['trip_creation_day'].astype('int8')
df2['trip_creation_day'].head()
```

Out[43]:
```
0    12
1    12
2    12
3    12
4    12
Name: trip_creation_day, dtype: int8
```

In [44]:
```
df2['trip_creation_month'] = df2['trip_creation_time'].dt.month
df2['trip_creation_month'] = df2['trip_creation_month'].astype('int8')
df2['trip_creation_month'].head()
```

Out[44]:
```
0    9
1    9
2    9
3    9
4    9
Name: trip_creation_month, dtype: int8
```

In [45]:
```
df2['trip_creation_year'] = df2['trip_creation_time'].dt.year
df2['trip_creation_year'] = df2['trip_creation_year'].astype('int16')
df2['trip_creation_year'].head()
```

Out[45]:
```
0    2018
1    2018
2    2018
3    2018
4    2018
Name: trip_creation_year, dtype: int16
```

In [46]:
```
df2['trip_creation_week'] = df2['trip_creation_time'].dt.isocalendar().week
df2['trip_creation_week'] = df2['trip_creation_week'].astype('int8')
df2['trip_creation_week'].head()
```

Out[46]:
```
0    37
1    37
2    37
3    37
4    37
Name: trip_creation_week, dtype: int8
```

In [47]:
```
df2['trip_creation_hour'] = df2['trip_creation_time'].dt.hour
df2['trip_creation_hour'] = df2['trip_creation_hour'].astype('int8')
df2['trip_creation_hour'].head()
```

Out[47]:
```
0    0
1    0
2    0
3    0
4    0
Name: trip_creation_hour, dtype: int8
```

Finding the structure of data after data cleaning

In [48]:
```
df2.shape
```

Out[48]:
```
(14817, 29)
```

In [49]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14817 entries, 0 to 14816
Data columns (total 29 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  float32
 11  actual_time                     14817 non-null  float32
 12  osrm_time                       14817 non-null  float32
 13  osrm_distance                   14817 non-null  float32
 14  segment_actual_time             14817 non-null  float32
 15  segment_osrm_time               14817 non-null  float32
 16  segment_osrm_distance           14817 non-null  float32
 17  source_state                    14817 non-null  object
 18  source_city                     14817 non-null  object
 19  source_place                    14817 non-null  object
 20  destination_state               14817 non-null  object
 21  destination_city                14817 non-null  object
 22  destination_place               14817 non-null  object
 23  trip_creation_date              14817 non-null  datetime64[ns]
 24  trip_creation_day               14817 non-null  int8
 25  trip_creation_month             14817 non-null  int8
 26  trip_creation_year              14817 non-null  int16
 27  trip_creation_week              14817 non-null  int8
 28  trip_creation_hour              14817 non-null  int8
dtypes: category(2), datetime64[ns](2), float32(7), float64(2), int16(1), int8(4), object(11)
memory usage: 2.2+ MB
```

In [50]:
```
df2.describe().T
```

Out[50]:

	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	164.477951	305.388123	9.002461	22.837238	48.474072	164.583206	2186.531738
actual_time	14817.0	357.143768	561.395020	9.000000	67.000000	149.000000	370.000000	6265.000000
osrm_time	14817.0	161.384018	271.362549	6.000000	29.000000	60.000000	168.000000	2032.000000
osrm_distance	14817.0	204.345078	370.395508	9.072900	30.819201	65.618805	208.475006	2840.081055
segment_actual_time	14817.0	353.892273	556.246826	9.000000	66.000000	147.000000	367.000000	6230.000000
segment_osrm_time	14817.0	180.949783	314.541412	6.000000	31.000000	65.000000	185.000000	2564.000000
segment_osrm_distance	14817.0	223.201324	416.628326	9.072900	32.654499	70.154404	218.802399	3523.632324
trip_creation_day	14817.0	18.370790	7.893275	1.000000	14.000000	19.000000	25.000000	30.000000
trip_creation_month	14817.0	9.120672	0.325757	9.000000	9.000000	9.000000	9.000000	10.000000
trip_creation_year	14817.0	2018.000000	0.000000	2018.000000	2018.000000	2018.000000	2018.000000	2018.000000
trip_creation_week	14817.0	38.295944	0.967872	37.000000	38.000000	38.000000	39.000000	40.000000
trip_creation_hour	14817.0	12.449821	7.986553	0.000000	4.000000	14.000000	20.000000	23.000000

In [51]:
```
df2.describe(include = object).T
```
Out[51]:

	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	761	Bilaspur_HB	1063
destination_state	14817	39	Maharashtra	2561
destination_city	14817	806	Mumbai	1548
destination_place	14817	850	Bilaspur_HB	821

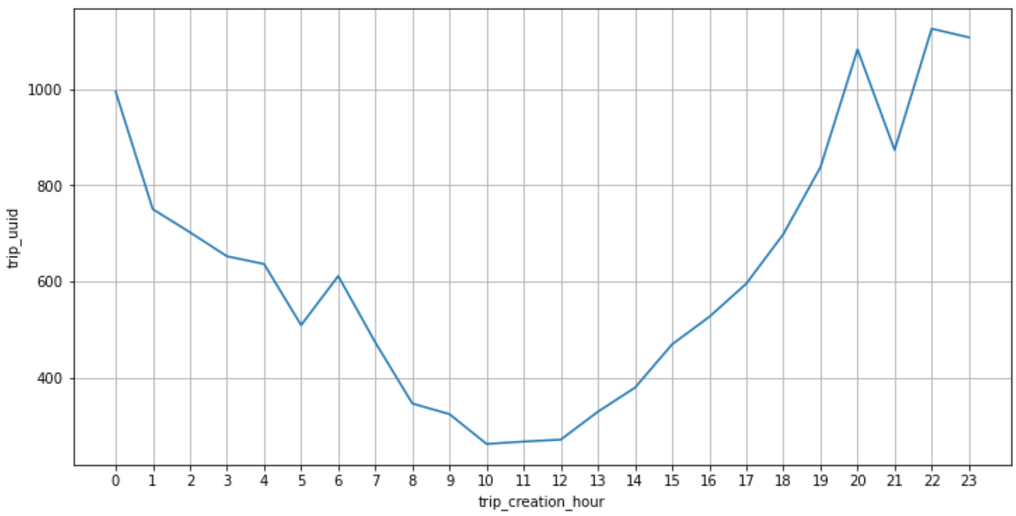
I am intrested to know how many trips are created on the hourly basis

In [52]:
```
df2['trip_creation_hour'].unique()
```
Out[52]:
```
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=int8)
```

In [53]:
```
df_hour = df2.groupby(by = 'trip_creation_hour')['trip_uuid'].count().to_frame().reset_index()
df_hour.head()
```
Out[53]:

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

In [54]:
```
plt.figure(figsize = (12, 6))
sns.lineplot(data = df_hour,
             x = df_hour['trip_creation_hour'],
             y = df_hour['trip_uuid'],
             markers = '*')
plt.xticks(np.arange(0,24))
plt.grid('both')
plt.plot()
```
Out[54]: []



- 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.

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

In [55]:
```
df2['trip_creation_day'].unique()
```

Out[55]:
```
array([12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28,
       29, 30,  1,  2,  3], dtype=int8)
```

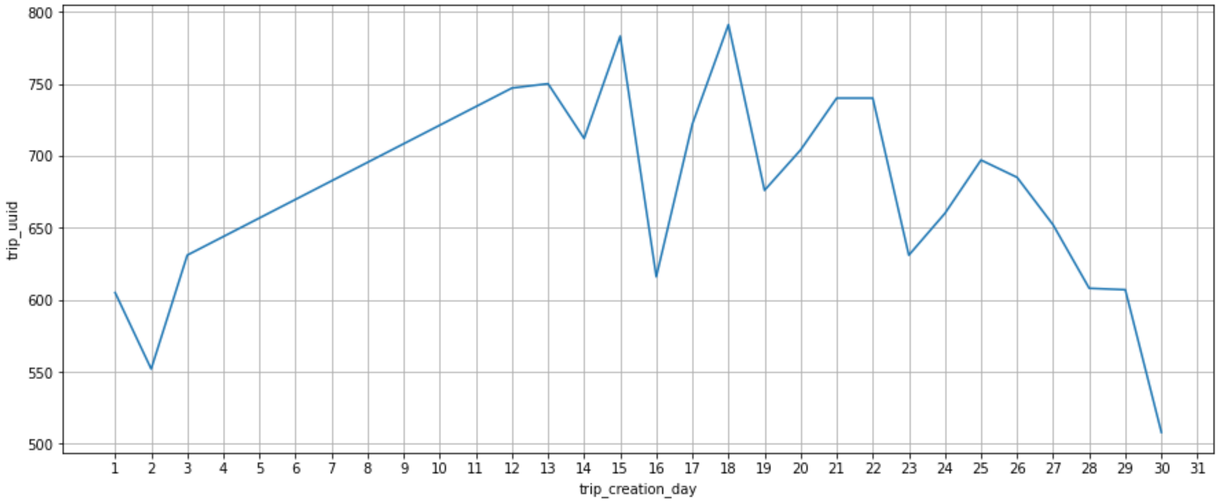
In [56]:
```
df_day = df2.groupby(by = 'trip_creation_day')['trip_uuid'].count().to_frame().reset_index()
df_day.head()
```

Out[56]:

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

In [57]:
```
plt.figure(figsize = (15, 6))
sns.lineplot(data = df_day,
             x = df_day['trip_creation_day'],
             y = df_day['trip_uuid'],
             markers = 'o')
plt.xticks(np.arange(1, 32))
plt.grid('both')
plt.plot()
```

Out[57]: []



- 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.

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

In [58]:
```
df2['trip_creation_week'].unique()
```

Out[58]:
```
array([37, 38, 39, 40], dtype=int8)
```

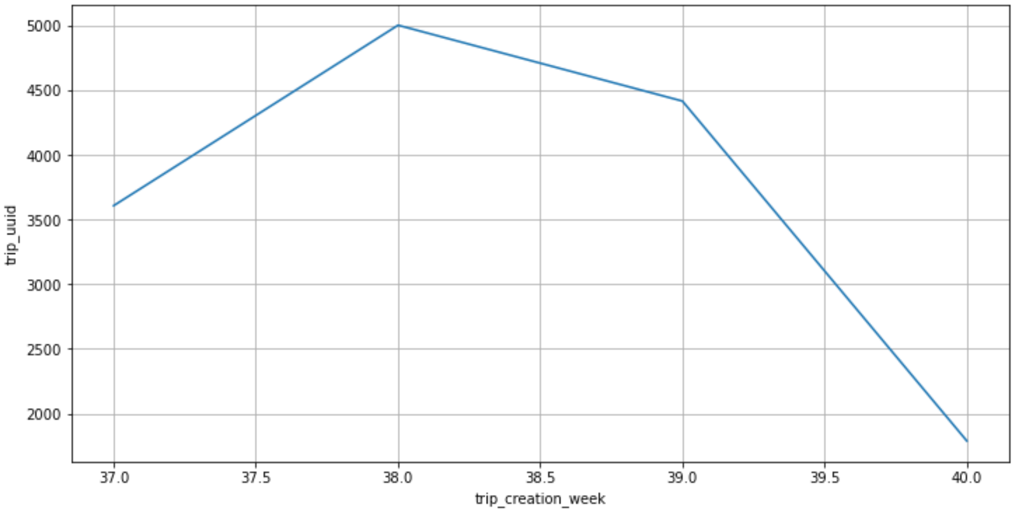
In [59]:
```
df_week = df2.groupby(by = 'trip_creation_week')['trip_uuid'].count().to_frame().reset_index()
df_week.head()
```

Out[59]:

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

In [60]:
```python
plt.figure(figsize = (12, 6))
sns.lineplot(data = df_week,
             x = df_week['trip_creation_week'],
             y = df_week['trip_uuid'],
             markers = 'o')
plt.grid('both')
plt.plot()
```

Out[60]: []



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

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

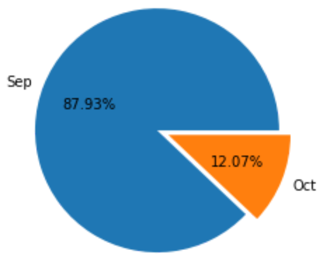
In [61]:
```python
df_month = df2.groupby(by = 'trip_creation_month')['trip_uuid'].count().to_frame().reset_index()
df_month['perc'] = np.round(df_month['trip_uuid'] * 100/ df_month['trip_uuid'].sum(), 2)
df_month.head()
```

Out[61]:

	trip_creation_month	trip_uuid	perc
0	9	13029	87.93
1	10	1788	12.07

In [62]:
```python
plt.pie(x = df_month['trip_uuid'],
        labels = ['Sep', 'Oct'],
        explode = [0, 0.1],
       autopct = '%.2f%%')
plt.plot()
```

Out[62]: []



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

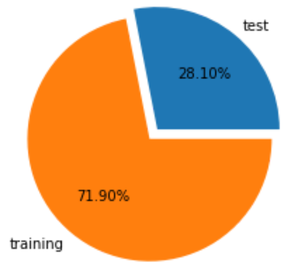
In [63]:
```
df_data = df2.groupby(by = 'data')['trip_uuid'].count().to_frame().reset_index()
df_data['perc'] = np.round(df_data['trip_uuid'] * 100/ df_data['trip_uuid'].sum(), 2)
df_data.head()
```

Out[63]:

	data	trip_uuid	perc
0	test	4163	28.1
1	training	10654	71.9

In [64]:
```
plt.pie(x = df_data['trip_uuid'],
        labels = df_data['data'],
        explode = [0, 0.1],
        autopct = '%.2f%%')
plt.plot()
```

Out[64]: []



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

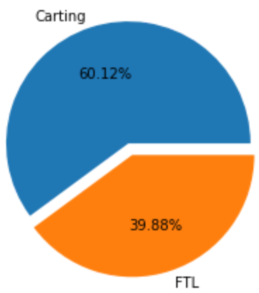
In [65]:
```
df_route = df2.groupby(by = 'route_type')['trip_uuid'].count().to_frame().reset_index()
df_route['perc'] = np.round(df_route['trip_uuid'] * 100/ df_route['trip_uuid'].sum(), 2)
df_route.head()
```

Out[65]:

	route_type	trip_uuid	perc
0	Carting	8908	60.12
1	FTL	5909	39.88

In [66]:
```
plt.pie(x = df_route['trip_uuid'],
        labels = ['Carting', 'FTL'],
        explode = [0, 0.1],
        autopct = '%.2f%%')
plt.plot()
```

Out[66]: []



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

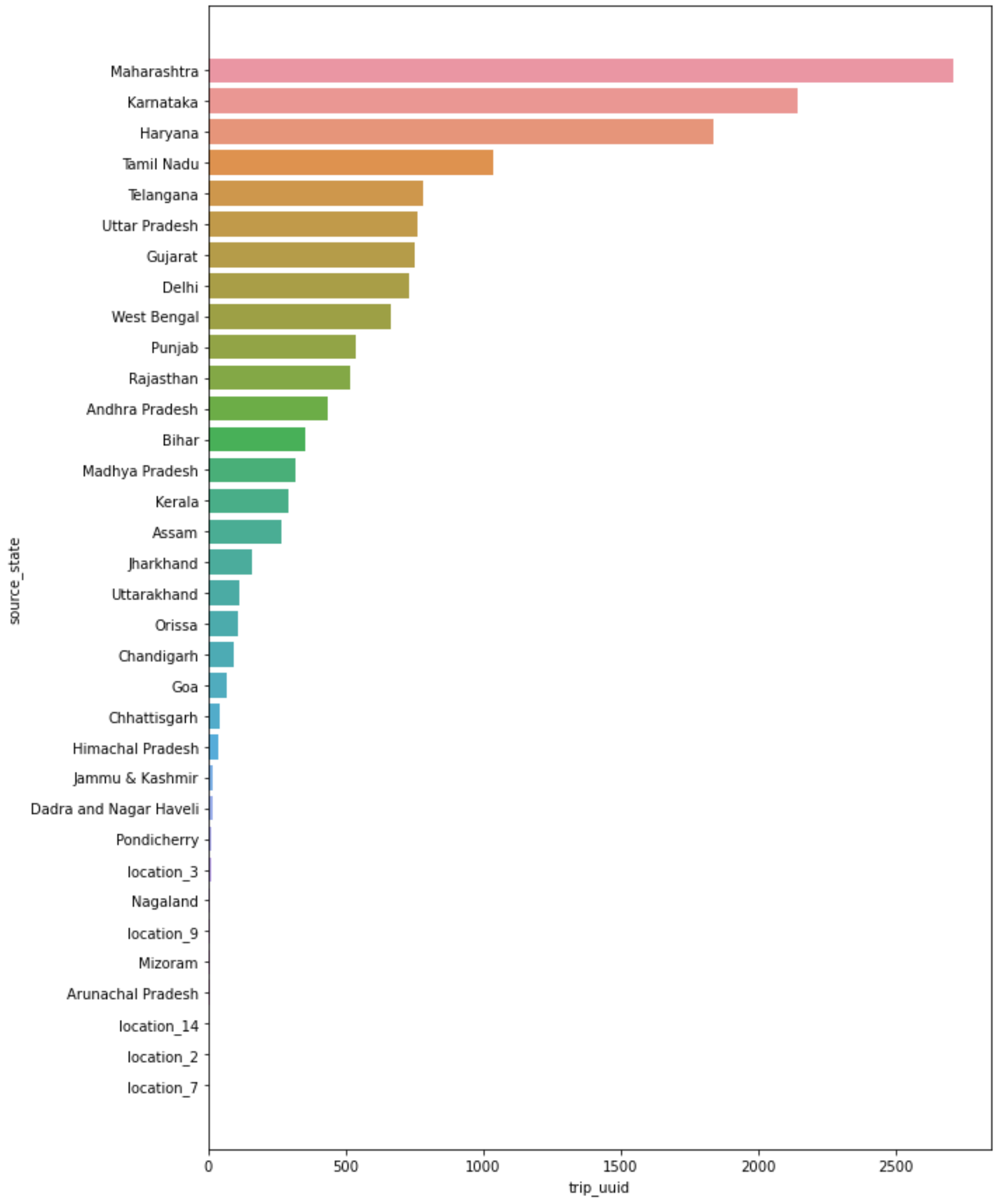
In [67]:
```
df_source_state = df2.groupby(by = 'source_state')['trip_uuid'].count().to_frame().reset_index()
df_source_state['perc'] = np.round(df_source_state['trip_uuid'] * 100/ df_source_state['trip_uuid'].sum(), 2)
df_source_state = df_source_state.sort_values(by = 'trip_uuid', ascending = False)
df_source_state.head()
```

Out[67]:

	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 [68]:
```
plt.figure(figsize = (10, 15))
sns.barplot(data = df_source_state,
            x = df_source_state['trip_uuid'],
            y = df_source_state['source_state'])
plt.plot()
```

Out[68]: []



- 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

I am interested to know top 30 cities based on the number of trips created from different cities

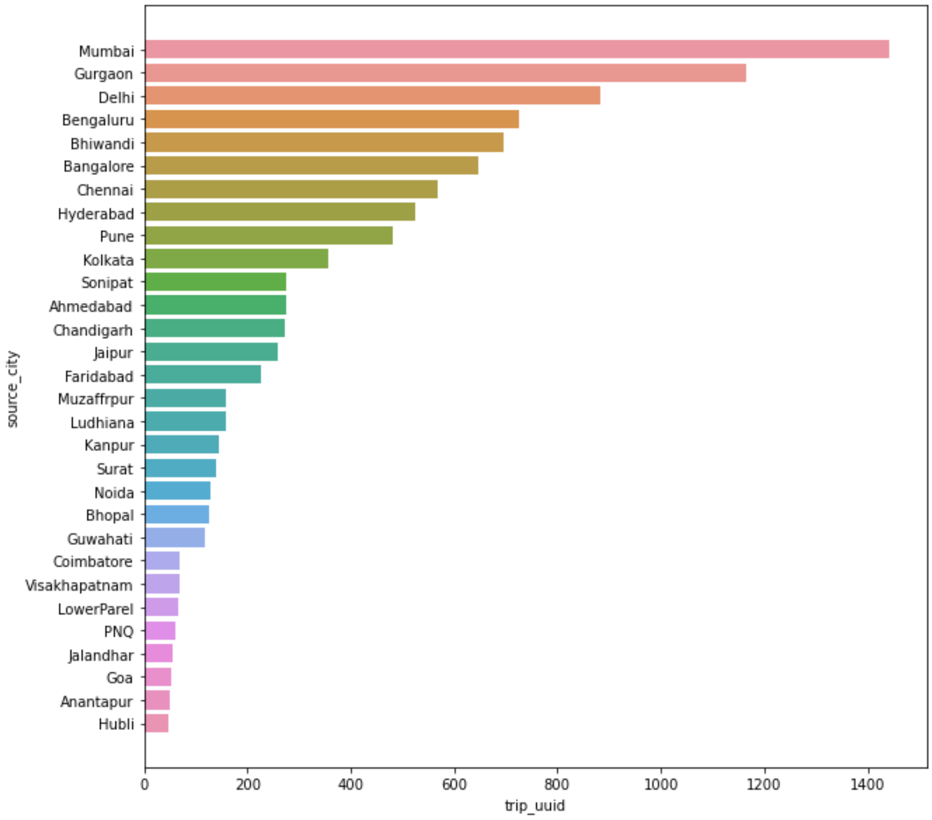
In [69]:
```python
df_source_city = df2.groupby(by = 'source_city')['trip_uuid'].count().to_frame().reset_index()
df_source_city['perc'] = np.round(df_source_city['trip_uuid'] * 100/ df_source_city['trip_uuid'].sum(), 2)
df_source_city = df_source_city.sort_values(by = 'trip_uuid', ascending = False)[:30]
df_source_city
```

Out[69]:

	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
58	Bangalore	648	4.37
136	Chennai	568	3.83
264	Hyderabad	524	3.54
516	Pune	480	3.24
357	Kolkata	356	2.40
610	Sonipat	276	1.86
2	Ahmedabad	274	1.85
133	Chandigarh	273	1.84
270	Jaipur	259	1.75
201	Faridabad	227	1.53
447	Muzaffrpur	159	1.07
382	Ludhiana	158	1.07
320	Kanpur	145	0.98
621	Surat	140	0.94
473	Noida	129	0.87
102	Bhopal	125	0.84
240	Guwahati	118	0.80
154	Coimbatore	69	0.47
679	Visakhapatnam	69	0.47
380	LowerParel	65	0.44
477	PNQ	62	0.42
273	Jalandhar	54	0.36
220	Goa	52	0.35
25	Anantapur	51	0.34
261	Hubli	47	0.32

In [70]:
```
plt.figure(figsize = (10, 10))
sns.barplot(data = df_source_city,
            x = df_source_city['trip_uuid'],
            y = df_source_city['source_city'])
plt.plot()
```

Out[70]: []



- 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.

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

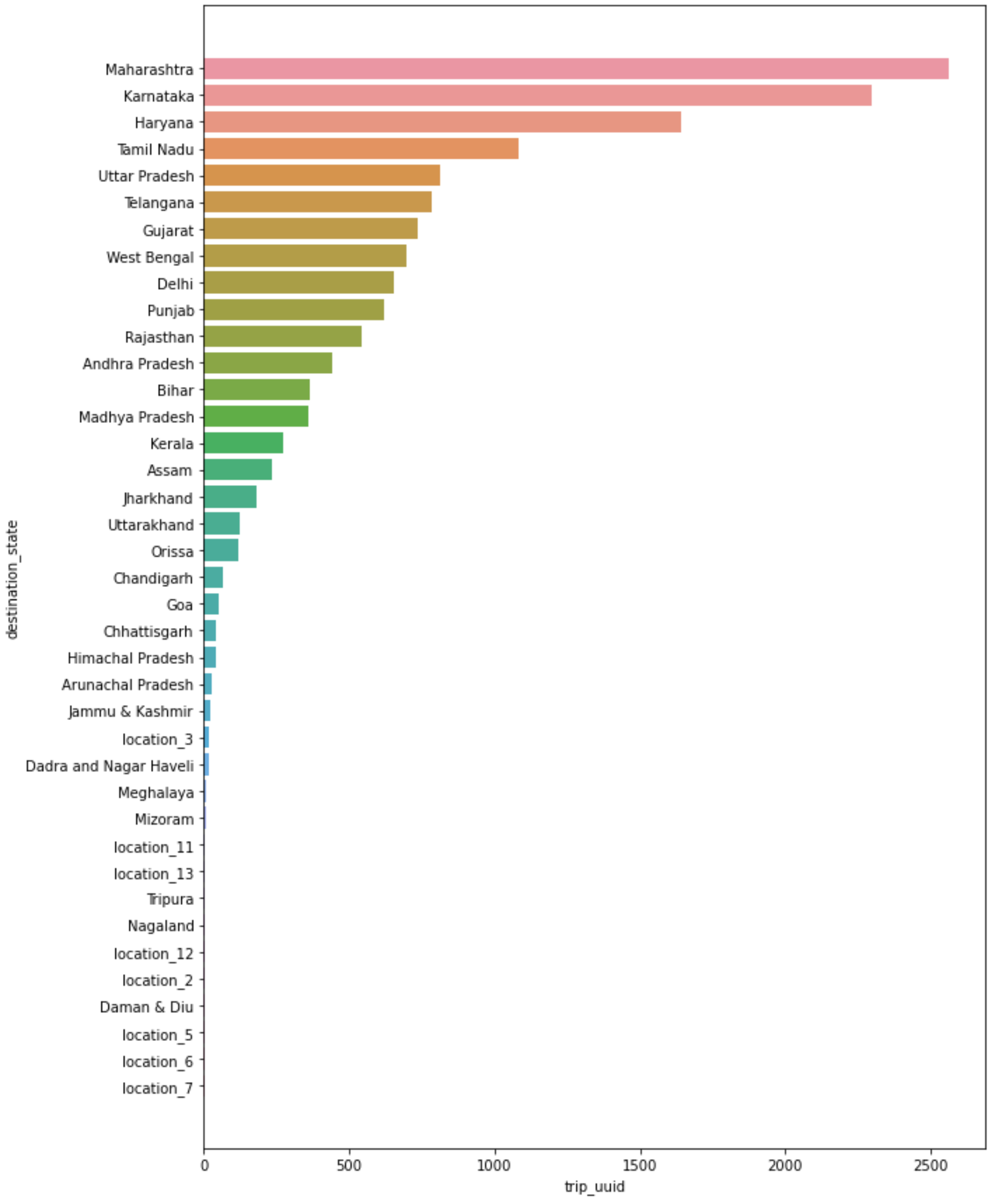
In [71]:
```
df_destination_state = df2.groupby(by = 'destination_state')['trip_uuid'].count().to_frame().reset_index()
df_destination_state['perc'] = np.round(df_destination_state['trip_uuid'] * 100/ df_destination_state['trip_uuid'].
df_destination_state = df_destination_state.sort_values(by = 'trip_uuid', ascending = False)
df_destination_state.head()
```

Out[71]:

	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 [72]:
```
plt.figure(figsize = (10, 15))
sns.barplot(data = df_destination_state,
            x = df_destination_state['trip_uuid'],
            y = df_destination_state['destination_state'])
plt.plot()
```

Out[72]: []



- 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.

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

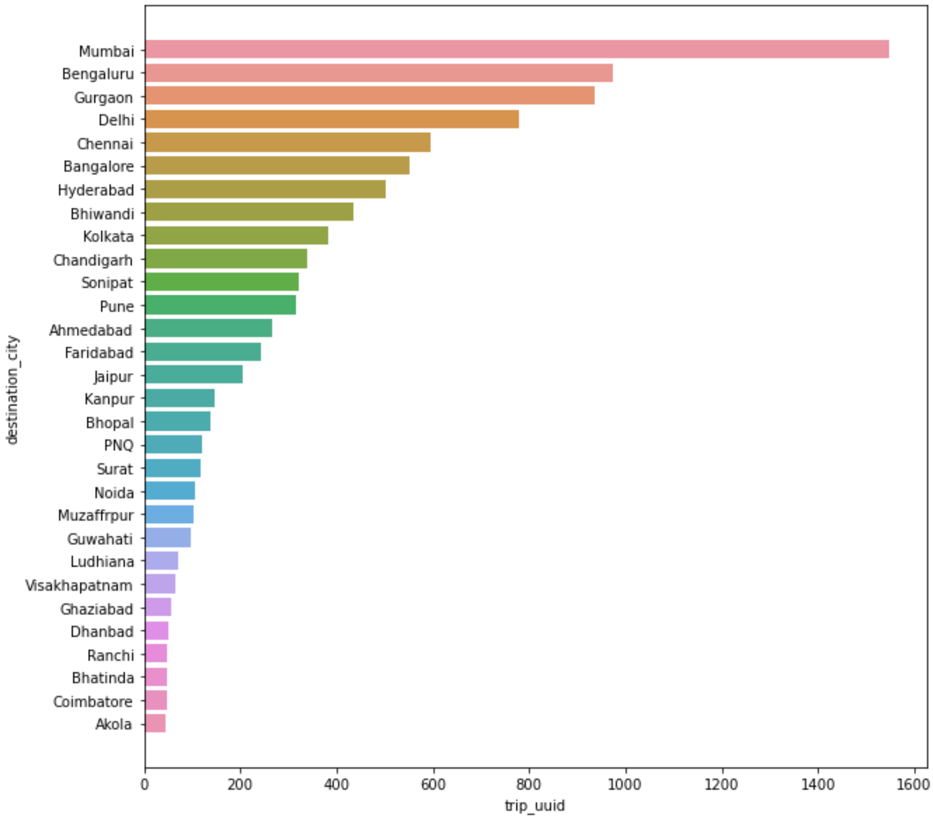
In [73]:
```
df_destination_city = df2.groupby(by = 'destination_city')['trip_uuid'].count().to_frame().reset_index()
df_destination_city['perc'] = np.round(df_destination_city['trip_uuid'] * 100/ df_destination_city['trip_uuid'].sum
df_destination_city = df_destination_city.sort_values(by = 'trip_uuid', ascending = False)[:30]
df_destination_city
```

Out[73]:

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

In [74]:
```
plt.figure(figsize = (10, 10))
sns.barplot(data = df_destination_city,
            x = df_destination_city['trip_uuid'],
            y = df_destination_city['destination_city'])
plt.plot()
```

Out[74]: []



- 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.

```
In [75]: 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[75]: []
```

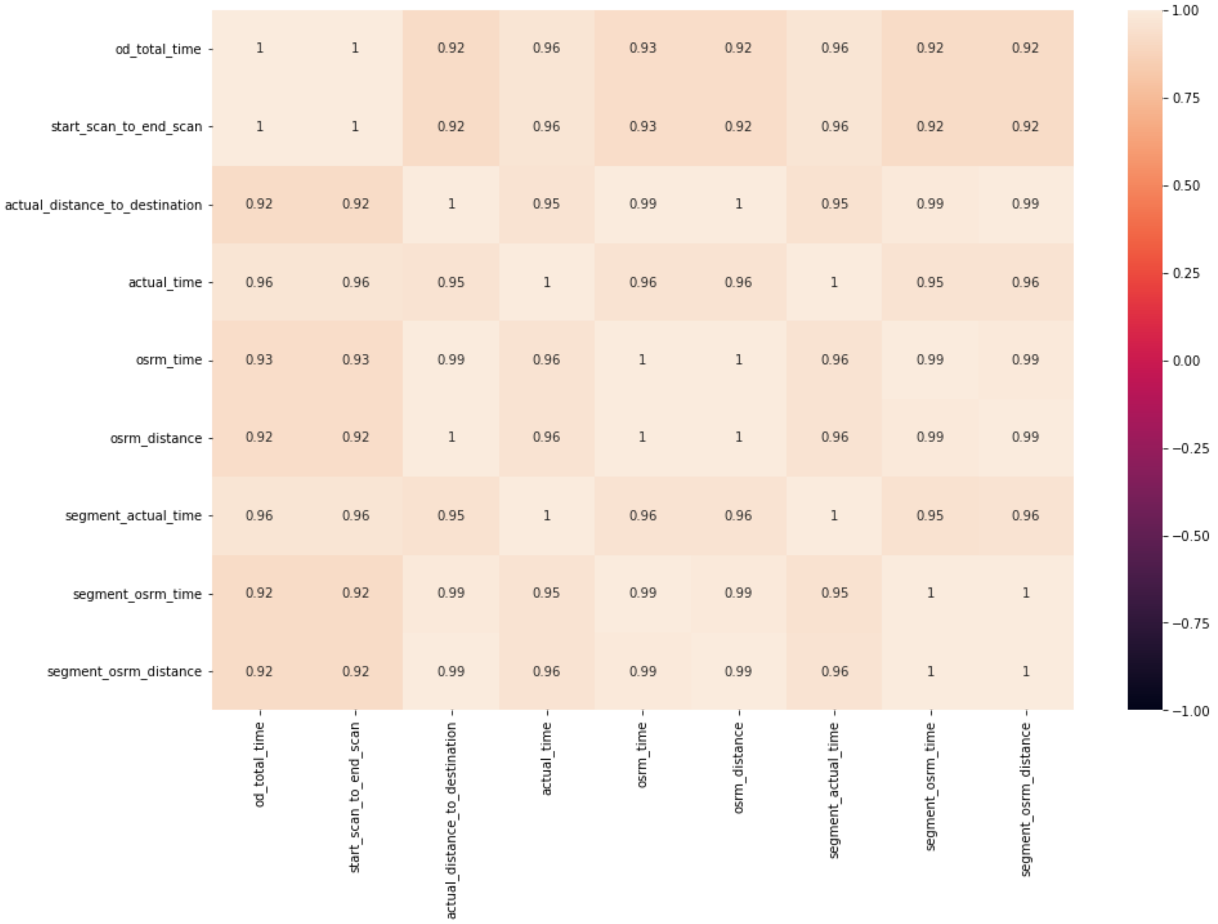

```
In [76]: df_corr = df2[numerical_columns].corr()
         df_corr
```

Out[76]:

	od_total_time	start_scan_to_end_scan	actual_distance_to_destination	actual_time	osrm_time	osrm_distance	s
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 [77]:
```
plt.figure(figsize = (15, 10))
sns.heatmap(data = df_corr, vmin = -1, vmax = 1, annot = True)
plt.plot()
```

Out[77]: []



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

3. In-depth analysis and feature engineering:

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

STEP-1 : Set up Null Hypothesis

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

STEP-2 : Checking for basic assumpitons for the hypothesis

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

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

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

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

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

STEP-5: Compare p-value and alpha.

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

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

In [78]:
```
df2[['od_total_time', 'start_scan_to_end_scan']].describe()
```

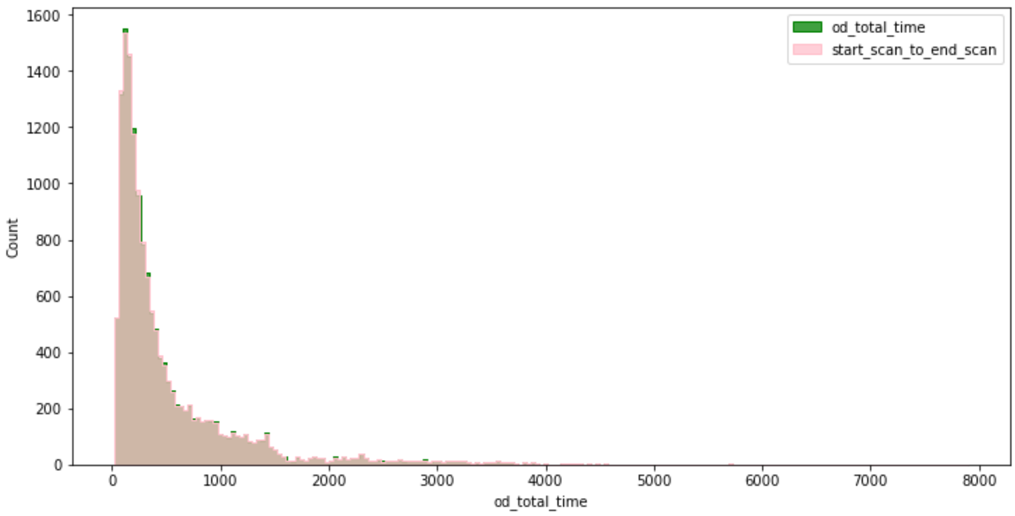
Out[78]:

	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

- Visual Tests to know if the samples follow normal distribution

In [79]:
```
plt.figure(figsize = (12, 6))
sns.histplot(df2['od_total_time'], element = 'step', color = 'green')
sns.histplot(df2['start_scan_to_end_scan'], element = 'step', color = 'pink')
plt.legend(['od_total_time', 'start_scan_to_end_scan'])
plt.plot()
```

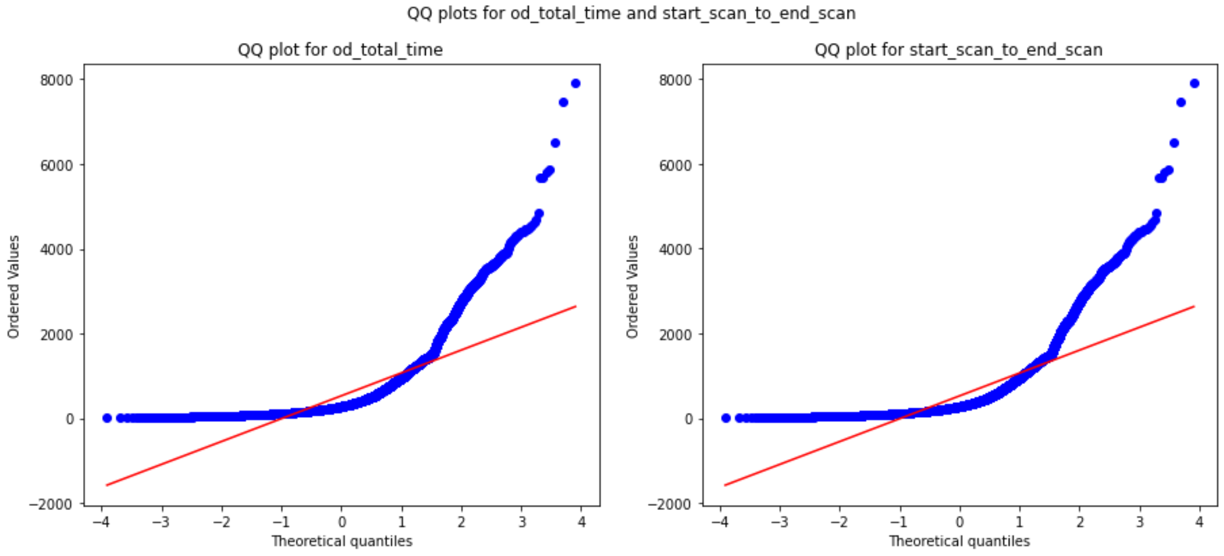
Out[79]: []



- Distribution check using **QQ Plot**

In [80]:
```python
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[80]: []



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

- Applying Shapiro-Wilk test for normality

H_0 : The sample **follows normal distribution** H_1 : The sample **does not follow normal distribution**

alpha = 0.05

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

In [81]:
```python
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 [82]:
```python
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 [83]:
```python
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 7.21300687930395e-25
The sample does not follow normal distribution
```

In [84]:
```
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 1.0378319150112312e-24
The sample does not follow normal distribution
```

- 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.

- Homogeneity of Variances using **Lavene's test**

In [85]:
```
# 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 [86]:
```
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
```

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

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

In [87]:
```
df2[['actual_time', 'osrm_time']].describe()
```

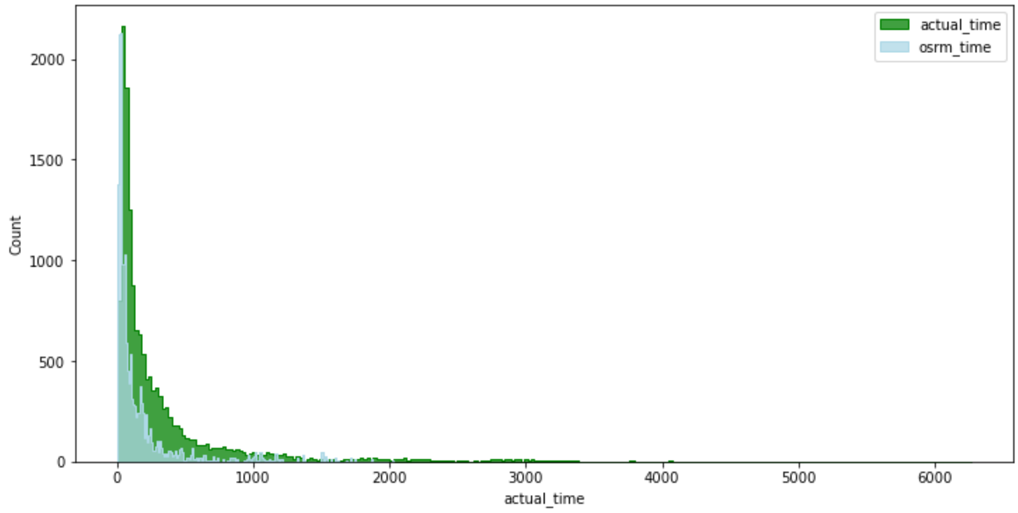
Out[87]:

	actual_time	osrm_time
count	14817.000000	14817.000000
mean	357.143768	161.384018
std	561.395020	271.362549
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

- Visual Tests to know if the samples follow normal distribution

```
In [88]: plt.figure(figsize = (12, 6))
sns.histplot(df2['actual_time'], element = 'step', color = 'green')
sns.histplot(df2['osrm_time'], element = 'step', color = 'lightblue')
plt.legend(['actual_time', 'osrm_time'])
plt.plot()
```

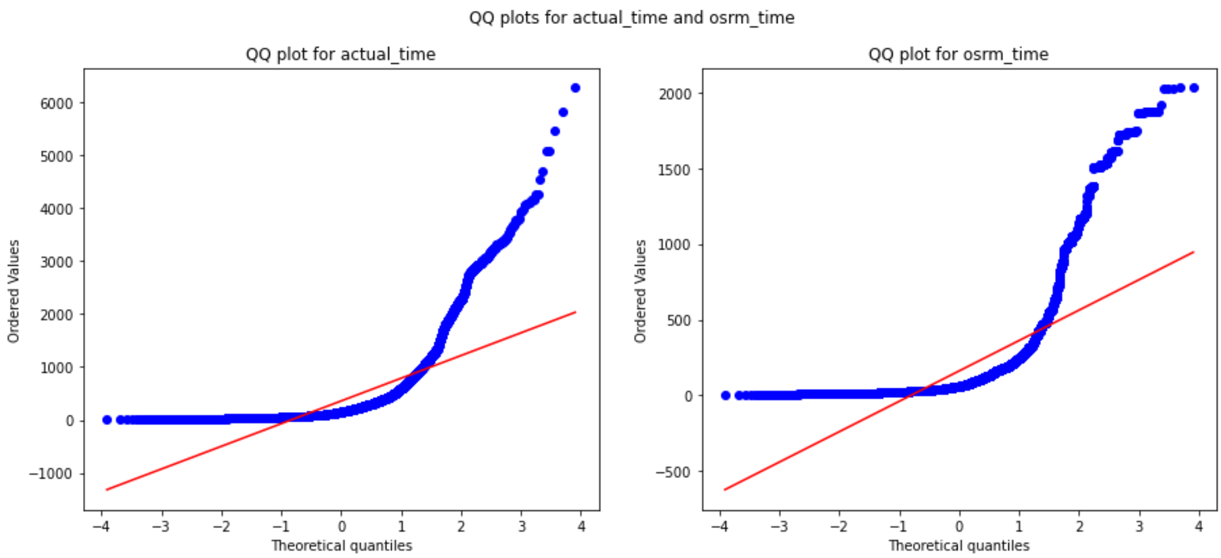
Out[88]: []



- Distribution check using **QQ Plot**

```
In [89]: 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[89]: []



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

- Applying Shapiro-Wilk test for normality

H_0 : The sample **follows normal distribution** H_1 : The sample **does not follow normal distribution**

alpha = 0.05

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

In [90]:
```
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 [91]:
```
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 [92]:
```
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 1.0408425976485893e-28
The sample does not follow normal distribution
```

In [93]:
```
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 3.271205914895016e-35
The sample does not follow normal distribution
```

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

- Homogeneity of Variances using **Lavene's test**

In [94]:
```
# 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 1.871098057987424e-220
The samples do not have  Homogenous Variance
```

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

In [95]:
```
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
```

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

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

In [96]:
```
df2[['actual_time', 'segment_actual_time']].describe()
```

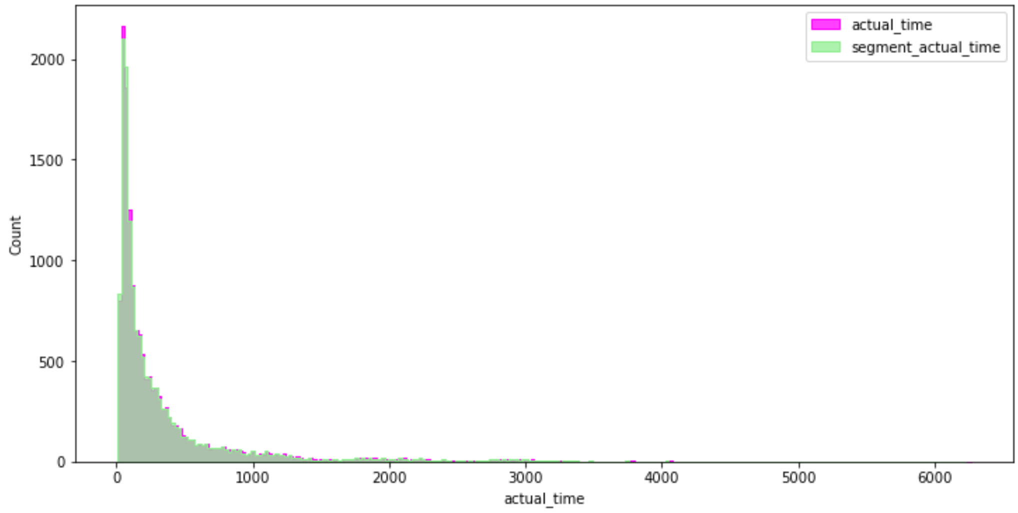
Out[96]:

	actual_time	segment_actual_time
count	14817.000000	14817.000000
mean	357.143768	353.892273
std	561.395020	556.246826
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

- Visual Tests to know if the samples follow normal distribution

In [97]:
```
plt.figure(figsize = (12, 6))
sns.histplot(df2['actual_time'], element = 'step', color = 'magenta')
sns.histplot(df2['segment_actual_time'], element = 'step', color = 'lightgreen')
plt.legend(['actual_time', 'segment_actual_time'])
plt.plot()
```

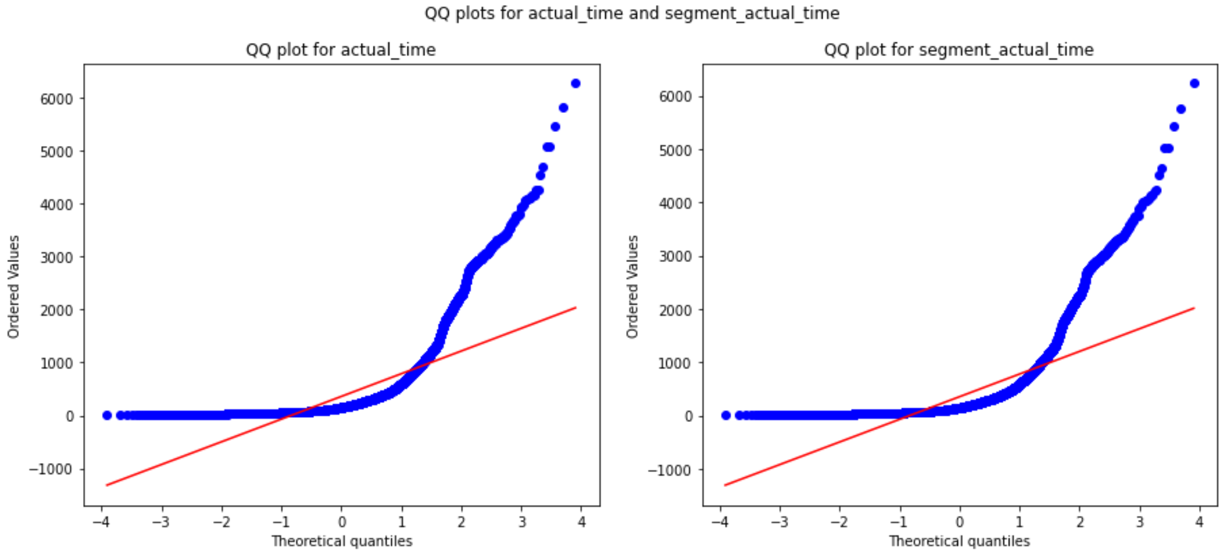
Out[97]: []



- Distribution check using **QQ Plot**

In [98]:
```
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[98]: []



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

- Applying Shapiro-Wilk test for normality

H_0 : The sample **follows normal distribution** H_1 : The sample **does not follow normal distribution**

alpha = 0.05

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

In [99]:
```
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 [100]:
```
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 [101]:
```
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 1.0408425976485893e-28
The sample does not follow normal distribution
```

In [102]:
```
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 5.676203648979465e-29
The sample does not follow normal distribution
```

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

- Homogeneity of Variances using **Lavene's test**

In [103]:
```
# 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 0.695502241317651
The samples have Homogenous Variance
```

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

In [104]:
```
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
```

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

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

In [105]:
```
df2[['osrm_distance', 'segment_osrm_distance']].describe()
```

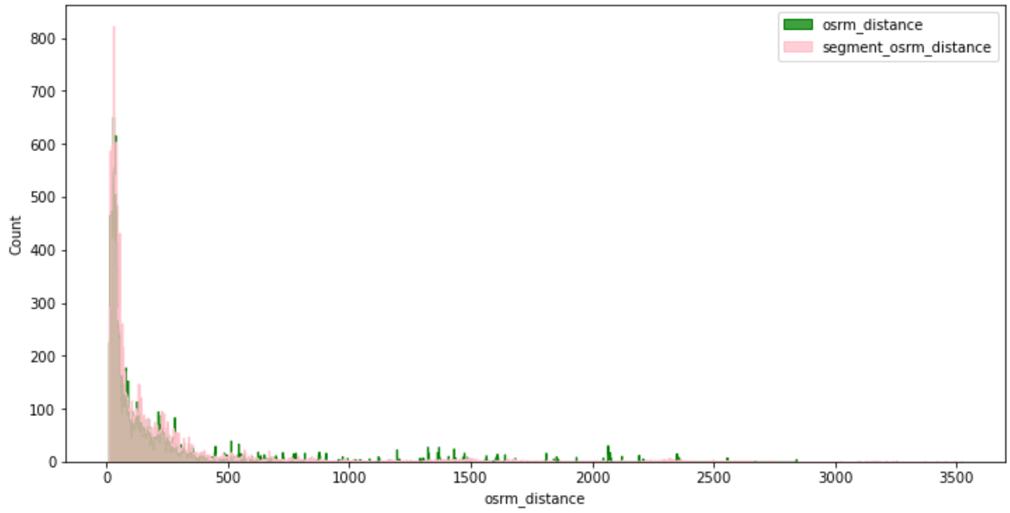
Out[105]:

	osrm_distance	segment_osrm_distance
count	14817.000000	14817.000000
mean	204.345078	223.201324
std	370.395508	416.628326
min	9.072900	9.072900
25%	30.819201	32.654499
50%	65.618805	70.154404
75%	208.475006	218.802399
max	2840.081055	3523.632324

- Visual Tests to know if the samples follow normal distribution

In [106]:
```
plt.figure(figsize = (12, 6))
sns.histplot(df2['osrm_distance'], element = 'step', color = 'green', bins = 1000)
sns.histplot(df2['segment_osrm_distance'], element = 'step', color = 'pink', bins = 1000)
plt.legend(['osrm_distance', 'segment_osrm_distance'])
plt.plot()
```

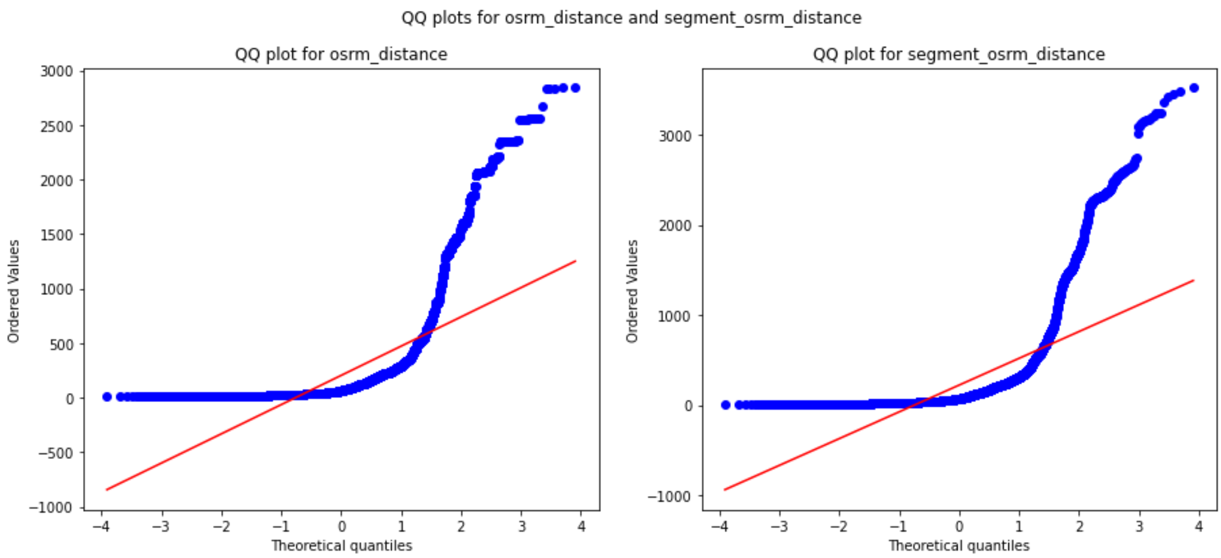
Out[106]: []



- Distribution check using **QQ Plot**

In [107]:
```
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[107]: []



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

- Applying Shapiro-Wilk test for normality

H_0 : The sample **follows normal distribution** H_1 : The sample **does not follow normal distribution**

alpha = 0.05

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

In [108]:
```
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 [109]:
```
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 [110]:
```
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 7.069971142058e-41
The sample does not follow normal distribution
```

In [111]:
```
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 3.0555416710688996e-38
The sample does not follow normal distribution
```

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

- Homogeneity of Variances using **Lavene's test**

In [112]:
```
# 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 0.00020976006524780905
The samples do not have Homogenous Variance
```

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

In [113]:
```
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 9.509312191161966e-07
The samples are not similar
```

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

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

In [114]:
```
df2[['osrm_time', 'segment_osrm_time']].describe().T
```

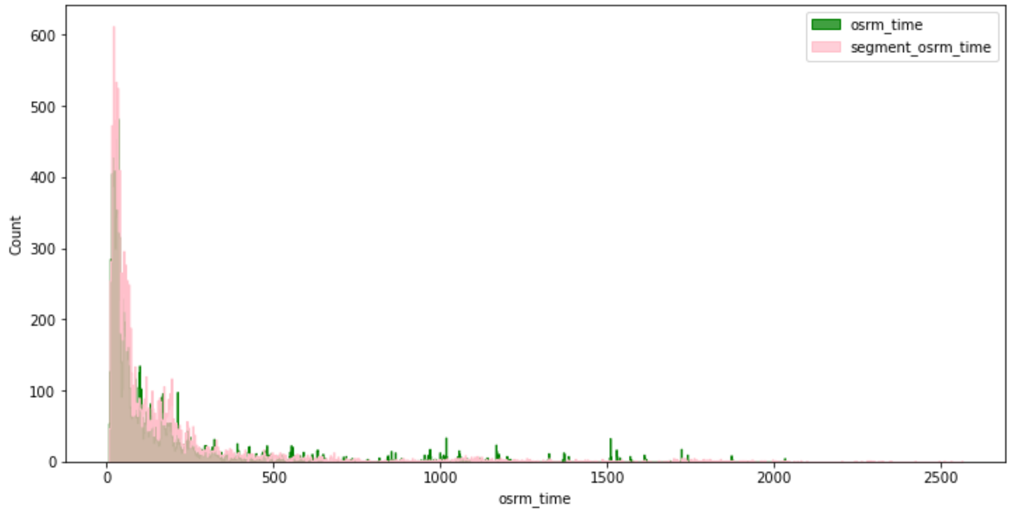
Out[114]:

	count	mean	std	min	25%	50%	75%	max
osrm_time	14817.0	161.384018	271.362549	6.0	29.0	60.0	168.0	2032.0
segment_osrm_time	14817.0	180.949783	314.541412	6.0	31.0	65.0	185.0	2564.0

- Visual Tests to know if the samples follow normal distribution

In [115]:
```
plt.figure(figsize = (12, 6))
sns.histplot(df2['osrm_time'], element = 'step', color = 'green', bins = 1000)
sns.histplot(df2['segment_osrm_time'], element = 'step', color = 'pink', bins = 1000)
plt.legend(['osrm_time', 'segment_osrm_time'])
plt.plot()
```

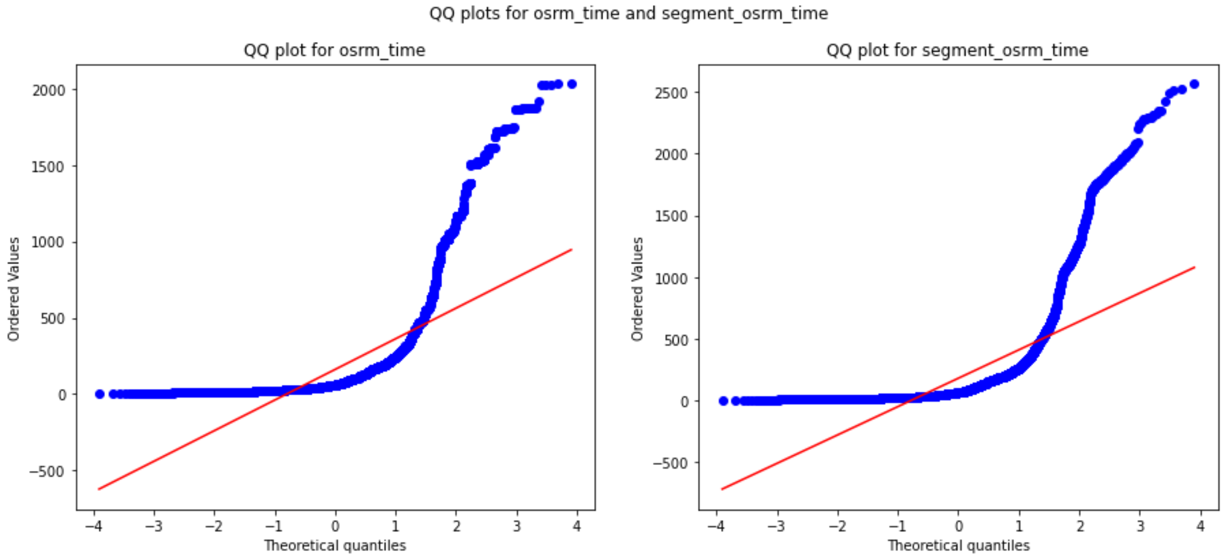
Out[115]: []



- Distribution check using **QQ Plot**

In [116]:
```
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[116]: []



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

- Applying Shapiro-Wilk test for normality

H_0 : The sample **follows normal distribution** H_1 : The sample **does not follow normal distribution**

alpha = 0.05

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

In [117]:
```
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 [118]:
```
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 [119]:
```
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 3.271205914895016e-35
The sample does not follow normal distribution
```

In [120]:
```
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 4.960995746782918e-34
The sample does not follow normal distribution
```

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

- Homogeneity of Variances using **Lavene's test**

In [121]:
```
# 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 8.349506135727595e-08
The samples do not have Homogenous Variance
```

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

In [122]:
```
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
```

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

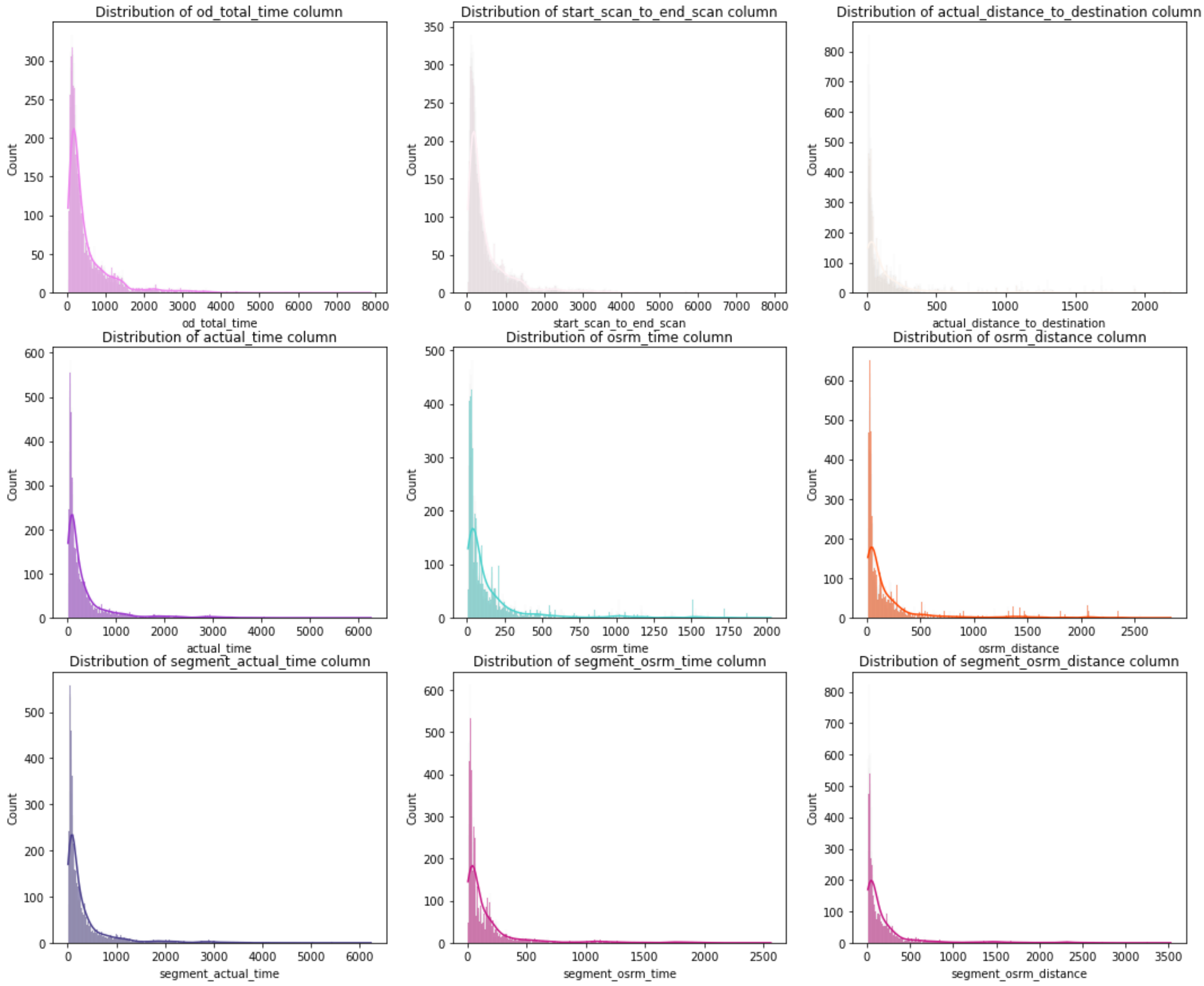
Find outliers in the numerical variables (you might find outliers in almost all the variables), and check it using visual analysis

In [123]:
```
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[123]:

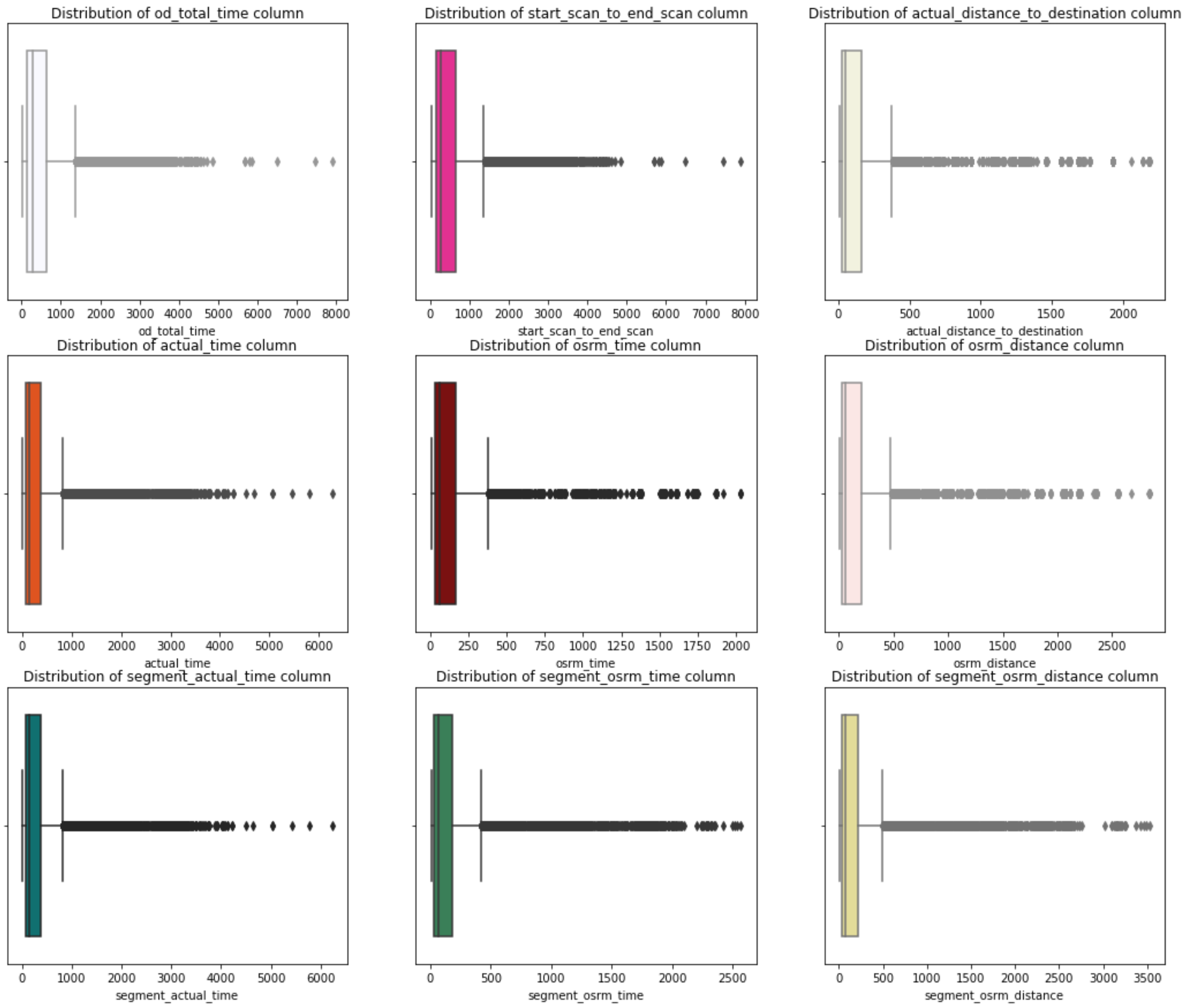
	count	mean	std	min	25%	50%	75%	max
od_total_time	14817.0	531.697630	658.868223	23.460000	149.930000	280.770000	638.200000	7898.550000
start_scan_to_end_scan	14817.0	530.810016	658.705957	23.000000	149.000000	280.000000	637.000000	7898.000000
actual_distance_to_destination	14817.0	164.477951	305.388123	9.002461	22.837238	48.474072	164.583206	2186.531738
actual_time	14817.0	357.143768	561.395020	9.000000	67.000000	149.000000	370.000000	6265.000000
osrm_time	14817.0	161.384018	271.362549	6.000000	29.000000	60.000000	168.000000	2032.000000
osrm_distance	14817.0	204.345078	370.395508	9.072900	30.819201	65.618805	208.475006	2840.081055
segment_actual_time	14817.0	353.892273	556.246826	9.000000	66.000000	147.000000	367.000000	6230.000000
segment_osrm_time	14817.0	180.949783	314.541412	6.000000	31.000000	65.000000	185.000000	2564.000000
segment_osrm_distance	14817.0	223.201324	416.628326	9.072900	32.654499	70.154404	218.802399	3523.632324

In [124]:
```
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()
```



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

In [125]:
```python
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.boxplot(df2[numerical_columns[i]], color = clr)
    plt.title(f"Distribution of {numerical_columns[i]} column")
    plt.plot()
```



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

In [126]:

```python
# 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 : 22.837238311767578
Q3 : 164.5832061767578
IQR : 141.74596786499023
LB : -189.78171348571777
UB : 377.20215797424316
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 : 30.81920051574707
Q3 : 208.47500610351562
IQR : 177.65580558776855
LB : -235.66450786590576
UB : 474.95871448516846
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 : 32.65449905395508
Q3 : 218.80239868164062
IQR : 186.14789962768555
LB : -246.56735038757324
UB : 498.02424812316895
Number of outliers : 1548
----------------------------------
```

The 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.

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

In [127]:
```
# Get value counts before one-hot encoding

df2['route_type'].value_counts()
```

Out[127]:
```
Carting    8908
FTL        5909
Name: route_type, dtype: int64
```

In [128]:
```
# Perform one-hot encoding on categorical column route type
```

In [129]:
```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
df2['route_type'] = label_encoder.fit_transform(df2['route_type'])
```

In [130]:
```
# Get value counts after one-hot encoding

df2['route_type'].value_counts()
```

Out[130]:
```
0    8908
1    5909
Name: route_type, dtype: int64
```

In [131]:
```
# Get value counts of categorical variable 'data' before one-hot encoding

df2['data'].value_counts()
```

Out[131]:
```
training    10654
test         4163
Name: data, dtype: int64
```

In [132]:
```
# Perform one-hot encoding on categorical variable 'data'
```

In [133]:
```
label_encoder = LabelEncoder()
df2['data'] = label_encoder.fit_transform(df2['data'])
```

In [134]:
```
# Get value counts after one-hot encoding

df2['data'].value_counts()
```

Out[134]:
```
1    10654
0     4163
Name: data, dtype: int64
```

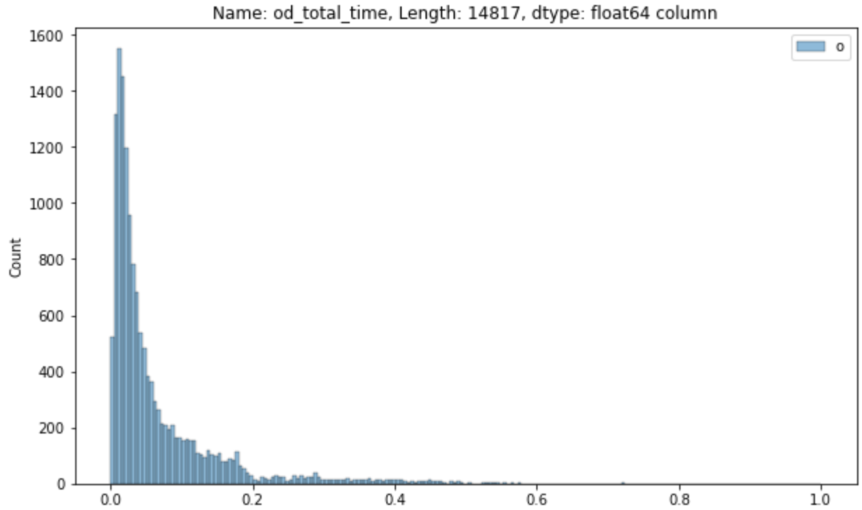
Normalize/ Standardize the numerical features using MinMaxScaler or StandardScaler.

In [135]:
```
from sklearn.preprocessing import MinMaxScaler
```

In [136]:
```python
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[136]: []

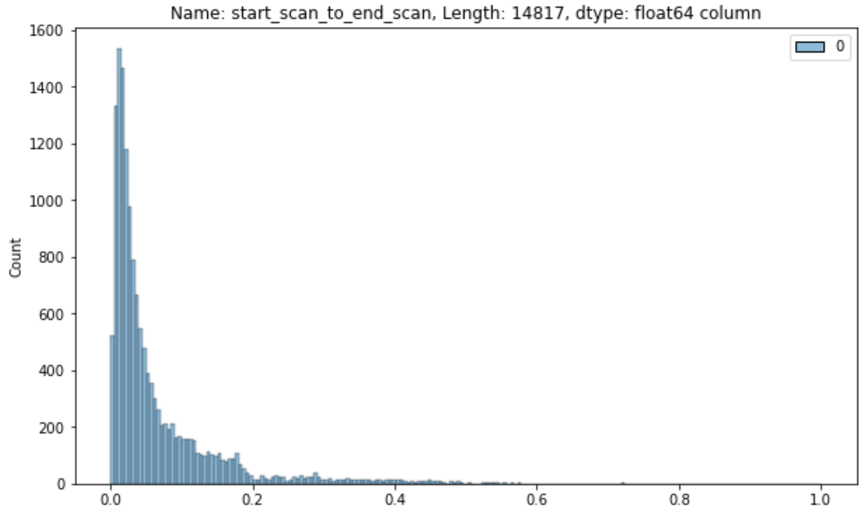
```
Normalized 0        2260.11
1         181.61
2        3934.36
3         100.49
4         718.34
          ...
14812     258.03
14813      60.59
14814     422.12
14815     348.52
14816     354.40
Name: od_total_time, Length: 14817, dtype: float64 column
```



In [137]:
```python
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()
```

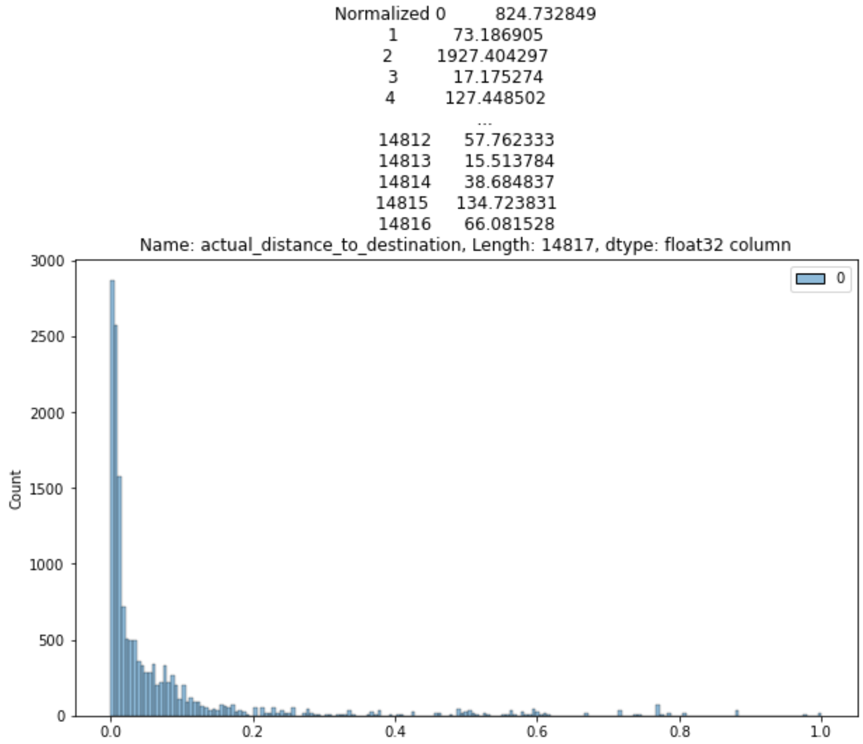
Out[137]: []

```
Normalized 0        2259.0
1         180.0
2        3933.0
3         100.0
4         717.0
          ...
14812     257.0
14813      60.0
14814     421.0
14815     347.0
14816     353.0
Name: start_scan_to_end_scan, Length: 14817, dtype: float64 column
```



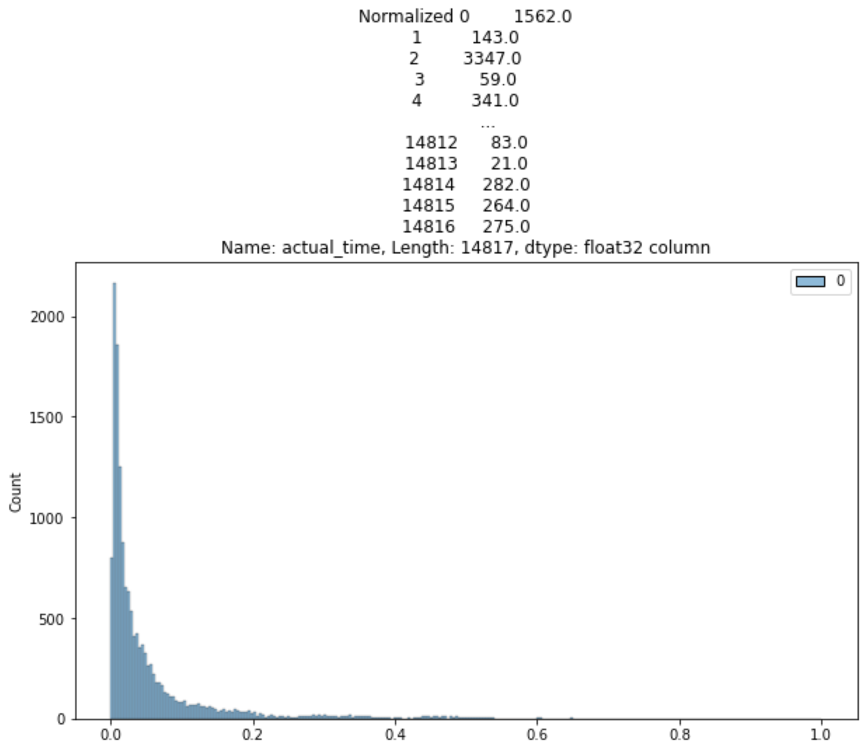
In [138]:
```python
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['actual_distance_to_destination'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['actual_distance_to_destination']} column")
plt.plot()
```

Out[138]: []



In [139]:
```python
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()
```

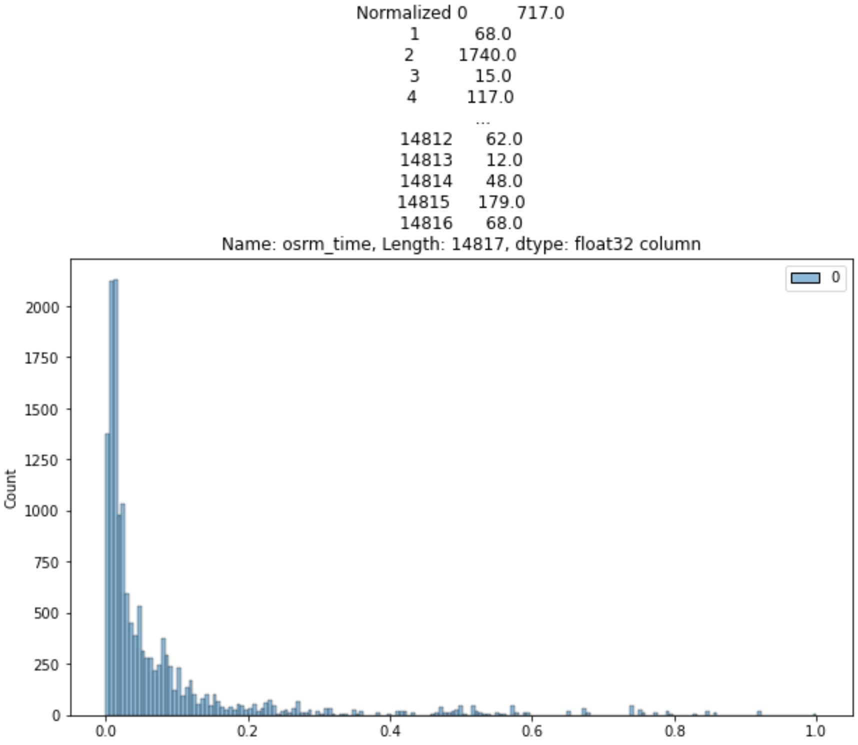
Out[139]: []



In [ ]:

In [140]:
```
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()
```

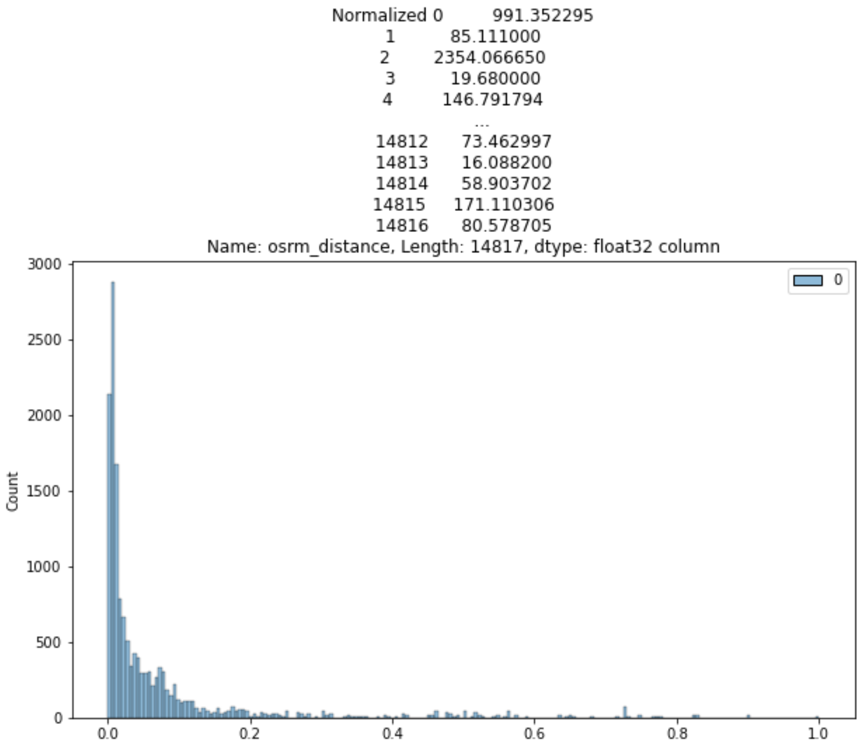
Out[140]: []



In [ ]:

In [141]:
```
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()
```

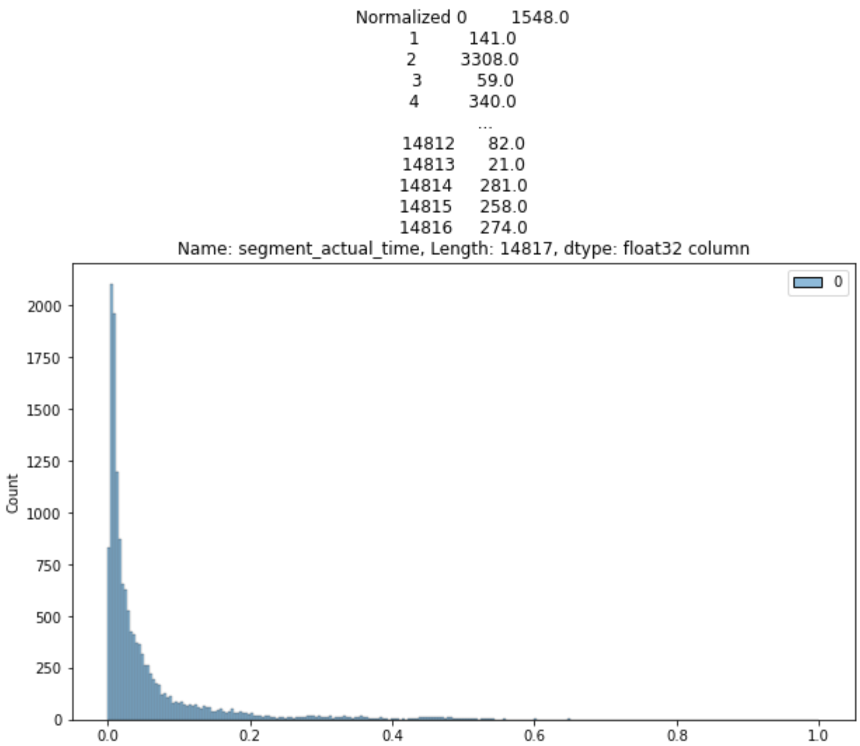
Out[141]: []



In [ ]:

In [142]:
```
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()
```

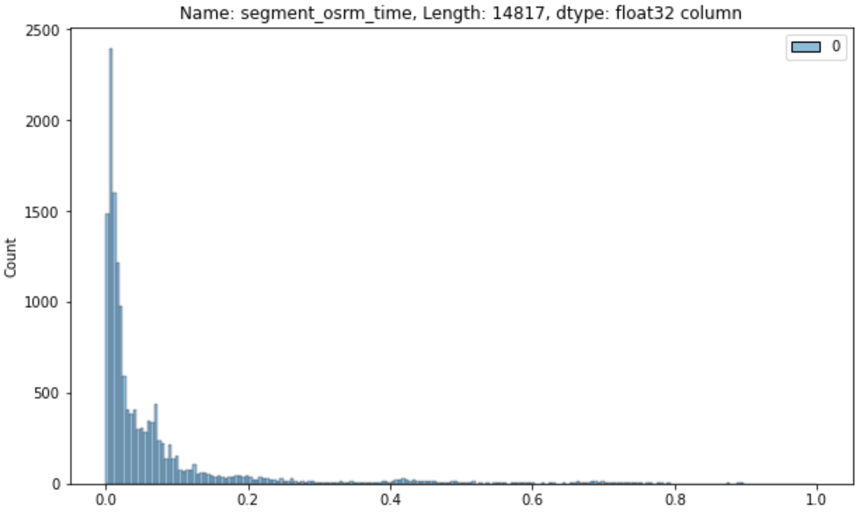
Out[142]: []



```
In [143]: 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[143]: []
```

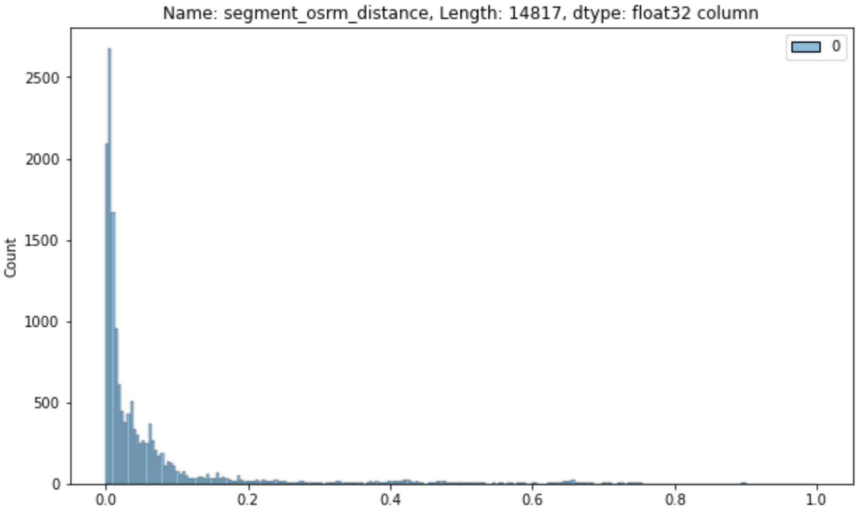
Normalized 0   1008.0
1   65.0
2   1941.0
3   16.0
4   115.0
...
14812   62.0
14813   11.0
14814   88.0
14815   221.0
14816   67.0
Name: segment_osrm_time, Length: 14817, dtype: float32 column




```
In [144]: 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[144]: []
```

Normalized 0   1320.473267
1   84.189400
2   2545.267822
3   19.876600
4   146.791901
...
14812   64.855103
14813   16.088299
14814   104.886597
14815   223.532410
14816   80.578705
Name: segment_osrm_distance, Length: 14817, dtype: float32 column

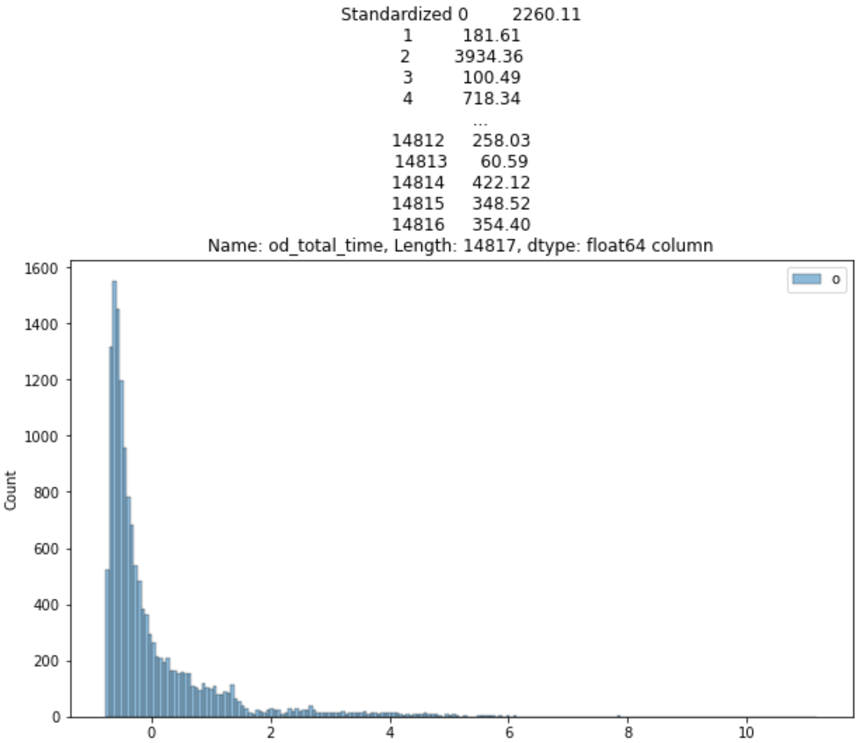


Column Standardization

In [145]:
```python
from sklearn.preprocessing import StandardScaler
```

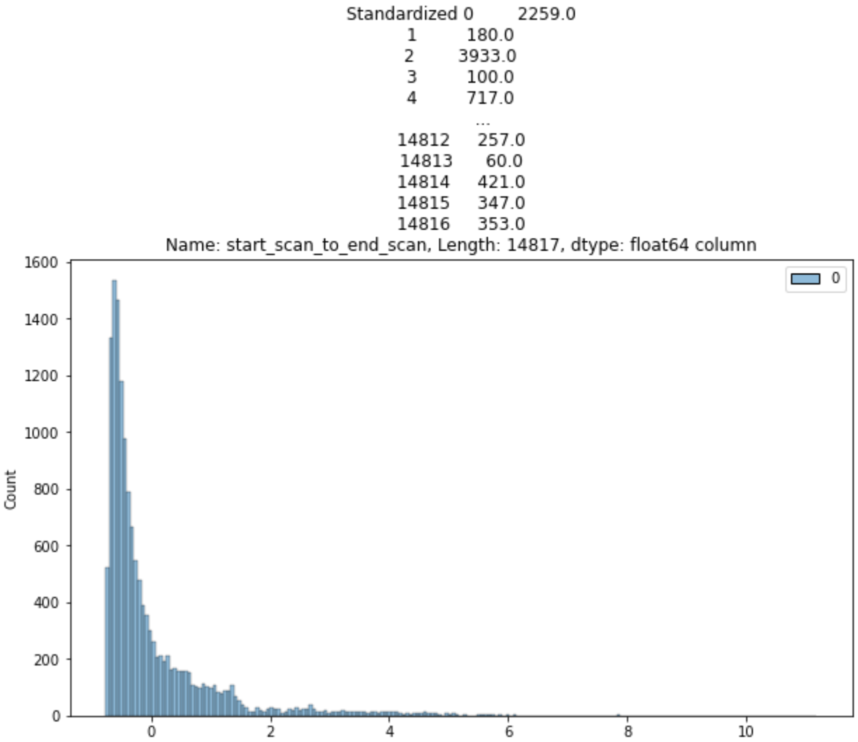
In [146]:
```python
plt.figure(figsize = (10, 6))
# define standard scaler
scaler = StandardScaler()
# transform data
scaled = scaler.fit_transform(df2['od_total_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['od_total_time']} column")
plt.legend('od_total_time')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

Out[146]: []



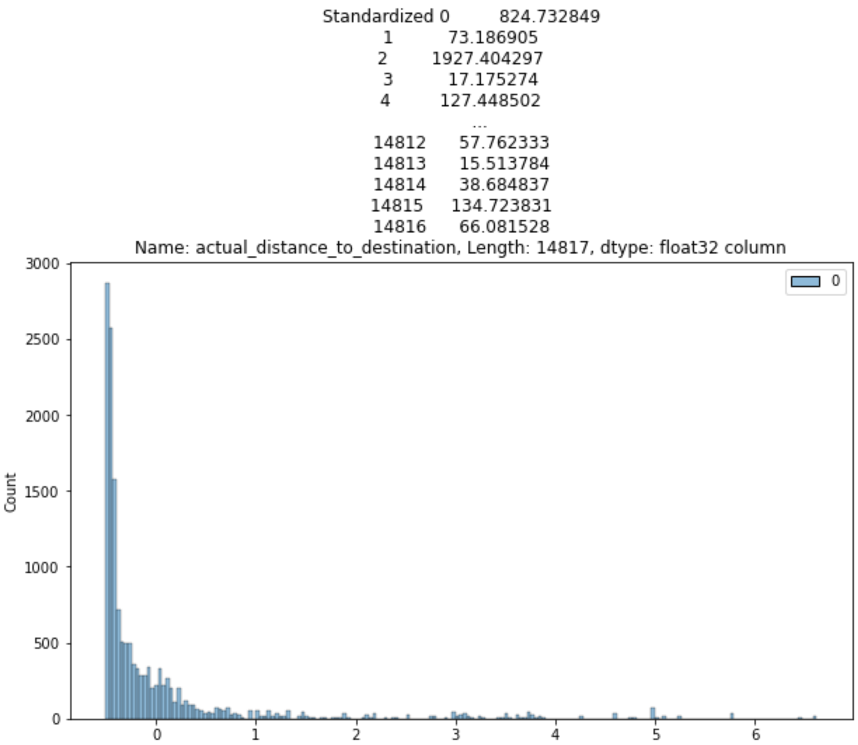
```
In [147]: plt.figure(figsize = (10, 6))
          scaler = StandardScaler()
          scaled = scaler.fit_transform(df2['start_scan_to_end_scan'].to_numpy().reshape(-1, 1))
          sns.histplot(scaled)
          plt.title(f"Standardized {df2['start_scan_to_end_scan']} column")
          plt.plot()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

```
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()
```

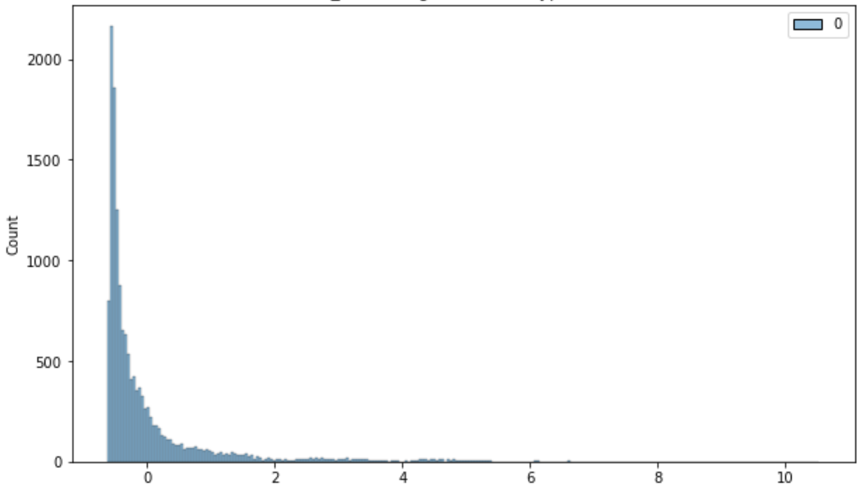
```
Out[148]: []
```



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]: []

```
Standardized 0        1562.0
1         143.0
2        3347.0
3          59.0
4         341.0
          ...
14812      83.0
14813      21.0
14814     282.0
14815     264.0
14816     275.0
Name: actual_time, Length: 14817, dtype: float32 column
```

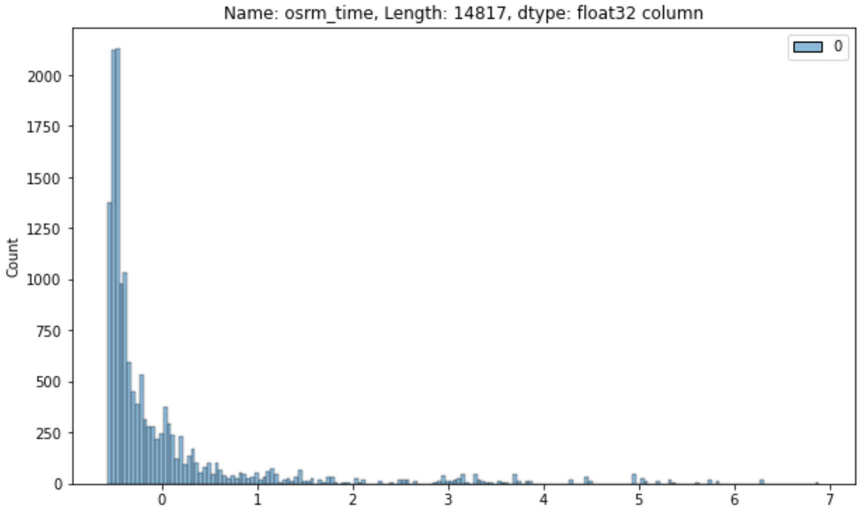


In [ ]:

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]: []

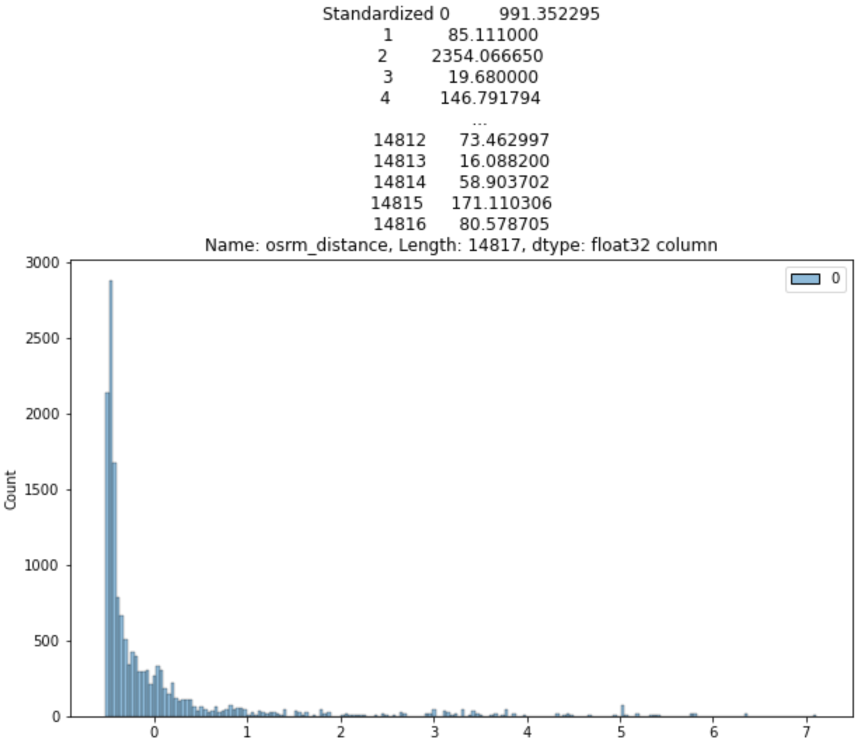
```
Standardized 0         717.0
1          68.0
2        1740.0
3          15.0
4         117.0
          ...
14812      62.0
14813      12.0
14814      48.0
14815     179.0
14816      68.0
Name: osrm_time, Length: 14817, dtype: float32 column
```



In [ ]:

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]: []

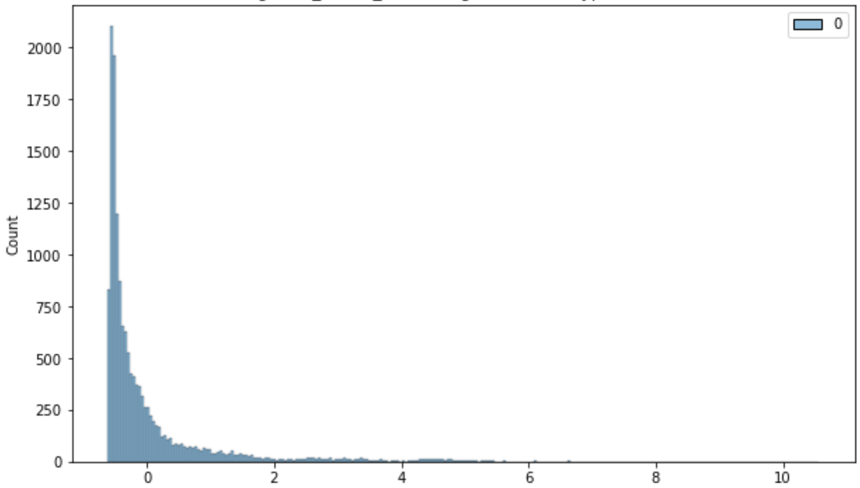


In [ ]:

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]: []

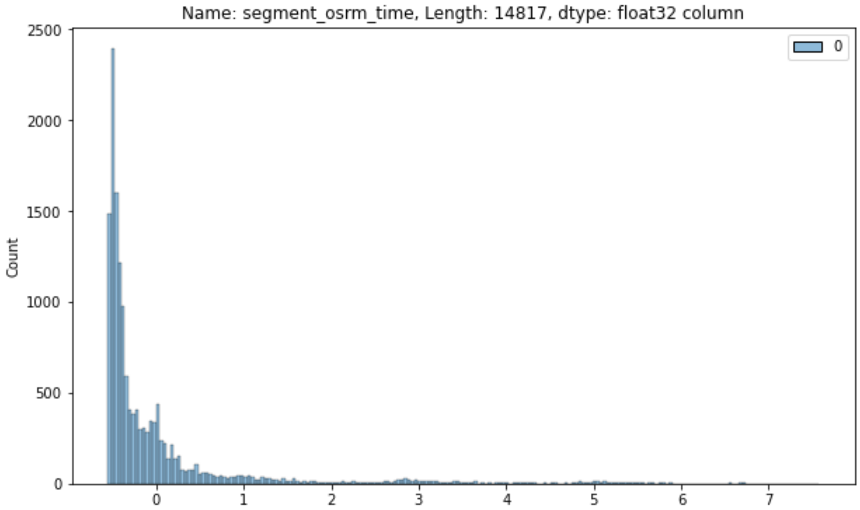
```
Standardized 0        1548.0
             1         141.0
             2        3308.0
             3          59.0
             4         340.0
                      ...
             14812      82.0
             14813      21.0
             14814     281.0
             14815     258.0
             14816     274.0
Name: segment_actual_time, Length: 14817, dtype: float32 column
```



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()
```

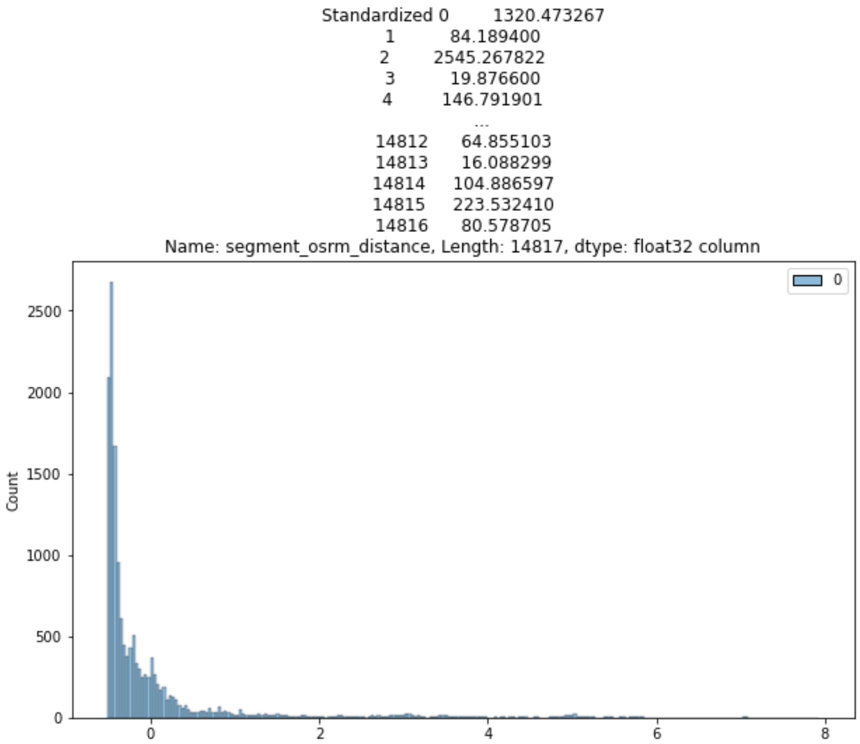
Out[153]: []

```
Standardized 0        1008.0
             1          65.0
             2        1941.0
             3          16.0
             4         115.0
                      ...
             14812      62.0
             14813      11.0
             14814      88.0
             14815     221.0
             14816      67.0
Name: segment_osrm_time, Length: 14817, dtype: float32 column
```



```
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]: []
```



Business 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.

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.

In [ ]:

```

```