Business Case: Delhivery

About Delhivery

Delhivery, India's leading and rapidly growing integrated player, has set its sights on creating the commerce operating system. They achieve this by utilizing world-class infrastructure, ensuring the highest quality in logistics operations, and harnessing cutting-edge engineering and technology capabilities.

Importing Required Libraries

```
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
```

Loading the Dataset

```
df =
pd.read_csv(r"https://d2beiqkhq929f0.cloudfront.net/public_assets/
assets/000/001/551/original/delhivery_data.csv?1642751181")

df.head()

       data          trip_creation_time  \
0  training  2018-09-20 02:35:36.476840
1  training  2018-09-20 02:35:36.476840
2  training  2018-09-20 02:35:36.476840
3  training  2018-09-20 02:35:36.476840
4  training  2018-09-20 02:35:36.476840

                                 route_schedule_uuid route_type  \
0  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...    Carting
1  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...    Carting
2  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...    Carting
3  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...    Carting
4  thanos::sroute:eb7bfc78-b351-4c0e-a951-fa3d5c3...    Carting

                 trip_uuid source_center
source_name  \
0  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)

1  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)

2  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)
```

```
3  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)

4  trip-153741093647649320  IND388121AAA  Anand_VUNagar_DC (Gujarat)


  destination_center               destination_name  \
0       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
1       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
2       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
3       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)
4       IND388620AAB  Khambhat_MotvdDPP_D (Gujarat)

                od_start_time  ...            cutoff_timestamp  \
0  2018-09-20 03:21:32.418600  ...         2018-09-20 04:27:55
1  2018-09-20 03:21:32.418600  ...         2018-09-20 04:17:55
2  2018-09-20 03:21:32.418600  ...  2018-09-20 04:01:19.505586
3  2018-09-20 03:21:32.418600  ...         2018-09-20 03:39:57
4  2018-09-20 03:21:32.418600  ...         2018-09-20 03:33:55

   actual_distance_to_destination  actual_time  osrm_time
osrm_distance  \
0                       10.435660         14.0       11.0
11.9653
1                       18.936842         24.0       20.0
21.7243
2                       27.637279         40.0       28.0
32.5395
3                       36.118028         62.0       40.0
45.5620
4                       39.386040         68.0       44.0
54.2181

     factor  segment_actual_time  segment_osrm_time
segment_osrm_distance  \
0  1.272727                 14.0               11.0
11.9653
1  1.200000                 10.0                9.0
9.7590
2  1.428571                 16.0                7.0
10.8152
3  1.550000                 21.0               12.0
13.0224
4  1.545455                  6.0                5.0
3.9153

   segment_factor
0        1.272727
1        1.111111
2        2.285714
3        1.750000
```

```
4        1.200000

[5 rows x 24 columns]
```

Shape of the loaded dataset

```
df.shape
```

```
(144867, 24)
```

columns present in the dataset

```
df.columns
```

```
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')
```

Basic Information about the Dataset

```
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

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

converting the datatype of columns

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

fc = ['actual_distance_to_destination', 'actual_time', 'osrm_time',
'osrm_distance',
                    'segment_actual_time', 'segment_osrm_time',
'segment_osrm_distance']

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

Updating the datatype of the datetime columns

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

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
```

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

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

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

1. Basic data cleaning and exploration:

Checking null values present in the dataset

```
df.isnull().sum()

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
```

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

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

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

```
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 ?

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

```
False
```

Treating missing destination names and source names

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

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
```

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

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

```
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

```
df.describe()
```

```
       start_scan_to_end_scan  actual_distance_to_destination
actual_time  \
count           144867.000000                   144867.000000
144867.000000
mean               961.262986                      234.073380
416.927521
std               1037.012769                      344.990021
598.103638
min                 20.000000                        9.000046
9.000000
25%                161.000000                       23.355875
51.000000
50%                449.000000                       66.126572
132.000000
```

```
75%                  1634.000000                         286.708878
513.000000
max                  7898.000000                        1927.447754
4532.000000

              osrm_time  osrm_distance  segment_actual_time
segment_osrm_time  \
count  144867.000000  144867.000000        144867.000000
144867.000000
mean      213.868286     284.771301            36.196110
18.507547
std       308.011078     421.119293            53.571156
14.775960
min         6.000000       9.008200          -244.000000
0.000000
25%        27.000000      29.914701            20.000000
11.000000
50%        64.000000      78.525803            29.000000
17.000000
75%       257.000000     343.193253            40.000000
22.000000
max      1686.000000    2326.199219          3051.000000
1611.000000

       segment_osrm_distance
count          144867.000000
mean               22.829018
std                17.860661
min                 0.000000
25%                12.070100
50%                23.513000
75%                27.813250
max              2191.403809
```

```python
df.describe(include = 'object')
```

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

                      trip_uuid source_center
source_name  \
count                    144867        144867
144867
unique                    14817          1508
1508
top     trip-153811219535896559  IND000000ACB  Gurgaon_Bilaspur_HB
(Haryana)
```

```
freq                                101         23347
23347

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

Merging of rows and aggregation of fields

```
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

                     trip_uuid source_center destination_center
data  \
0      trip-153671041653548748  IND209304AAA       IND000000ACB
training
1      trip-153671041653548748  IND462022AAA       IND209304AAA
training
```

```
2      trip-153671042288605164  IND561203AAB       IND562101AAA
training
3      trip-153671042288605164  IND572101AAA       IND561203AAB
training
4      trip-153671043369099517  IND000000ACB       IND160002AAC
training
...                       ...          ...                  ...
...
26363  trip-153861115439069069  IND628204AAA       IND627657AAA
test
26364  trip-153861115439069069  IND628613AAA       IND627005AAA
test
26365  trip-153861115439069069  IND628801AAA       IND628204AAA
test
26366  trip-153861118270144424  IND583119AAA       IND583101AAA
test
26367  trip-153861118270144424  IND583201AAA       IND583119AAA
test

      route_type         trip_creation_time  \
0            FTL 2018-09-12 00:00:16.535741
1            FTL 2018-09-12 00:00:16.535741
2        Carting 2018-09-12 00:00:22.886430
3        Carting 2018-09-12 00:00:22.886430
4            FTL 2018-09-12 00:00:33.691250
...          ...                        ...
26363    Carting 2018-10-03 23:59:14.390954
26364    Carting 2018-10-03 23:59:14.390954
26365    Carting 2018-10-03 23:59:14.390954
26366        FTL 2018-10-03 23:59:42.701692
26367        FTL 2018-10-03 23:59:42.701692

                                source_name  \
0      Kanpur_Central_H_6 (Uttar Pradesh)
1      Bhopal_Trnsport_H (Madhya Pradesh)
2       Doddablpur_ChikaDPP_D (Karnataka)
3           Tumkur_Veersagr_I (Karnataka)
4           Gurgaon_Bilaspur_HB (Haryana)
...                                   ...
26363  Tirchchndr_Shnmgprm_D (Tamil Nadu)
26364   Peikulam_SriVnktpm_D (Tamil Nadu)
26365         Eral_Busstand_D (Tamil Nadu)
26366        Sandur_WrdN1DPP_D (Karnataka)
26367                   Hospet (Karnataka)

                           destination_name
od_start_time  \
0               Gurgaon_Bilaspur_HB (Haryana) 2018-09-12
16:39:46.858469
1          Kanpur_Central_H_6 (Uttar Pradesh) 2018-09-12
```

```
00:00:16.535741
2          Chikblapur_ShntiSgr_D (Karnataka) 2018-09-12
02:03:09.655591
3          Doddablpur_ChikaDPP_D (Karnataka) 2018-09-12
00:00:22.886430
4             Chandigarh_Mehmdpur_H (Punjab) 2018-09-14
03:40:17.106733
...                                      ...                        ..
.
26363  Thisayanvilai_UdnkdiRD_D (Tamil Nadu) 2018-10-04
02:29:04.272194
26364    Tirunelveli_VdkkuSrt_I (Tamil Nadu) 2018-10-04
04:16:39.894872
26365     Tirchchndr_Shnmgprm_D (Tamil Nadu) 2018-10-04
01:44:53.808000
26366                Bellary_Dc (Karnataka) 2018-10-04
03:58:40.726547
26367          Sandur_WrdN1DPP_D (Karnataka) 2018-10-04
02:51:44.712656

                     od_end_time  start_scan_to_end_scan  \
0     2018-09-13 13:40:23.123744                  1260.0
1     2018-09-12 16:39:46.858469                   999.0
2     2018-09-12 03:01:59.598855                    58.0
3     2018-09-12 02:03:09.655591                   122.0
4     2018-09-14 17:34:55.442454                   834.0
...                          ...                     ...
26363 2018-10-04 03:31:11.183797                    62.0
26364 2018-10-04 05:47:45.162682                    91.0
26365 2018-10-04 02:29:04.272194                    44.0
26366 2018-10-04 08:46:09.166940                   287.0
26367 2018-10-04 03:58:40.726547                    66.0

       actual_distance_to_destination  actual_time  osrm_time
osrm_distance  \
0                          383.759155        732.0      329.0
446.549591
1                          440.973694        830.0      388.0
544.802673
2                           24.644020         47.0       26.0
28.199400
3                           48.542889         96.0       42.0
56.911598
4                          237.439606        611.0      212.0
281.210907
...                               ...          ...        ...
...
26363                       33.627182         51.0       41.0
42.521301
```

```
26364                          33.673836          90.0        48.0
40.608002
26365                          12.661944          30.0        14.0
16.018499
26366                          40.546738         233.0        42.0
52.530300
26367                          25.534794          42.0        26.0
28.048401

       segment_actual_time  segment_osrm_time  segment_osrm_distance
0                    728.0              534.0             670.620483
1                    820.0              474.0             649.852783
2                     46.0               26.0              28.199501
3                     95.0               39.0              55.989899
4                    608.0              231.0             317.740784
...                    ...                ...                    ...
26363                 49.0               42.0              42.143101
26364                 89.0               77.0              78.586899
26365                 29.0               14.0              16.018400
26366                233.0               42.0              52.530300
26367                 41.0               25.0              28.048401

[26368 rows x 18 columns]
```

Time taken between od_start_time and od_end_time and keep it as a feature.

```
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()
```

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

```
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
```

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

      route_type         trip_creation_time  \
0            FTL 2018-09-12 00:00:16.535741
```

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

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

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

       start_scan_to_end_scan  actual_distance_to_destination
actual_time  \
0                      2259.0                      824.732849
1562.0
1                       180.0                       73.186905
143.0
2                      3933.0                     1927.404297
3347.0
3                       100.0                       17.175274
59.0
4                       717.0                      127.448502
341.0
...                       ...                             ...
```

```
...
14812                       257.0                               57.762333
83.0
14813                        60.0                               15.513784
21.0
14814                       421.0                               38.684837
282.0
14815                       347.0                              134.723831
264.0
14816                       353.0                               66.081528
275.0

       osrm_time  osrm_distance  segment_actual_time
segment_osrm_time  \
0          717.0     991.352295               1548.0
1008.0
1           68.0      85.111000                141.0
65.0
2         1740.0    2354.066650               3308.0
1941.0
3           15.0      19.680000                 59.0
16.0
4          117.0     146.791794                340.0
115.0
...          ...            ...                  ...                  ..
.
14812       62.0      73.462997                 82.0
62.0
14813       12.0      16.088200                 21.0
11.0
14814       48.0      58.903702                281.0
88.0
14815      179.0     171.110306                258.0
221.0
14816       68.0      80.578705                274.0
67.0

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

```
[14817 rows x 17 columns]
```

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

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

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]

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]

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

```
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)
```

```
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
```

```
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)
```

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

```
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)

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

```
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
```

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

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

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

```
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

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

```
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]
```

```
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()
```

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

```
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()
```

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

```
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()
```

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

```
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()
```

```
0    37
1    37
2    37
3    37
4    37
Name: trip_creation_week, dtype: int8
```

```
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()
```

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

Finding the structure of data after data cleaning

```
df2.shape
```

```
(14817, 29)
```

```
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
```

```
df2.describe()
```

```
       od_total_time  start_scan_to_end_scan
actual_distance_to_destination  \
count   14817.000000            14817.000000
14817.000000
mean      531.697630              530.810016
164.477829
std       658.868223              658.705957
305.388153
min        23.460000               23.000000
9.002461
```

```
25%       149.930000              149.000000
22.837238
50%       280.770000              280.000000
48.474072
75%       638.200000              637.000000
164.583206
max      7898.550000             7898.000000
2186.531738

        actual_time     osrm_time  osrm_distance  segment_actual_time
\
count  14817.000000  14817.000000   14817.000000         14817.000000

mean     357.143768    161.384018     204.344711           353.892273

std      561.396118    271.360992     370.395569           556.247925

min        9.000000      6.000000       9.072900             9.000000

25%       67.000000     29.000000      30.819201            66.000000

50%      149.000000     60.000000      65.618805           147.000000

75%      370.000000    168.000000     208.475006           367.000000

max     6265.000000   2032.000000    2840.081055          6230.000000


       segment_osrm_time  segment_osrm_distance  trip_creation_day  \
count       14817.000000           14817.000000       14817.000000
mean          180.949783             223.201157          18.370790
std           314.542053             416.628387           7.893275
min             6.000000               9.072900           1.000000
25%            31.000000              32.654499          14.000000
50%            65.000000              70.154404          19.000000
75%           185.000000             218.802399          25.000000
max          2564.000000            3523.632324          30.000000

       trip_creation_month  trip_creation_year  trip_creation_week  \
count         14817.000000             14817.0        14817.000000
mean              9.120672              2018.0           38.295944
std               0.325757                 0.0            0.967872
min               9.000000              2018.0           37.000000
25%               9.000000              2018.0           38.000000
50%               9.000000              2018.0           38.000000
75%               9.000000              2018.0           39.000000
max              10.000000              2018.0           40.000000

       trip_creation_hour
count        14817.000000
```

```
mean              12.449821
std                7.986553
min                0.000000
25%                4.000000
50%               14.000000
75%               20.000000
max               23.000000
```

```
df2.describe(include = object)
```

```
                      trip_uuid source_center destination_center  \
count                     14817         14817              14817
unique                    14817           938               1042
top     trip-153671041653548748  IND000000ACB       IND000000ACB
freq                          1          1063                821

                          source_name
destination_name  \
count                           14817                              14817

unique                            938                               1042

top     Gurgaon_Bilaspur_HB (Haryana)  Gurgaon_Bilaspur_HB (Haryana)

freq                             1063                                821


       source_state source_city source_place destination_state  \
count         14817       14817        14817             14817
unique           34         690          761                39
top     Maharashtra      Mumbai  Bilaspur_HB       Maharashtra
freq           2714        1442         1063              2561

       destination_city destination_place
count             14817             14817
unique              806               850
top              Mumbai       Bilaspur_HB
freq               1548               821
```

```
df2['trip_creation_hour'].unique()
```

```
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)
```

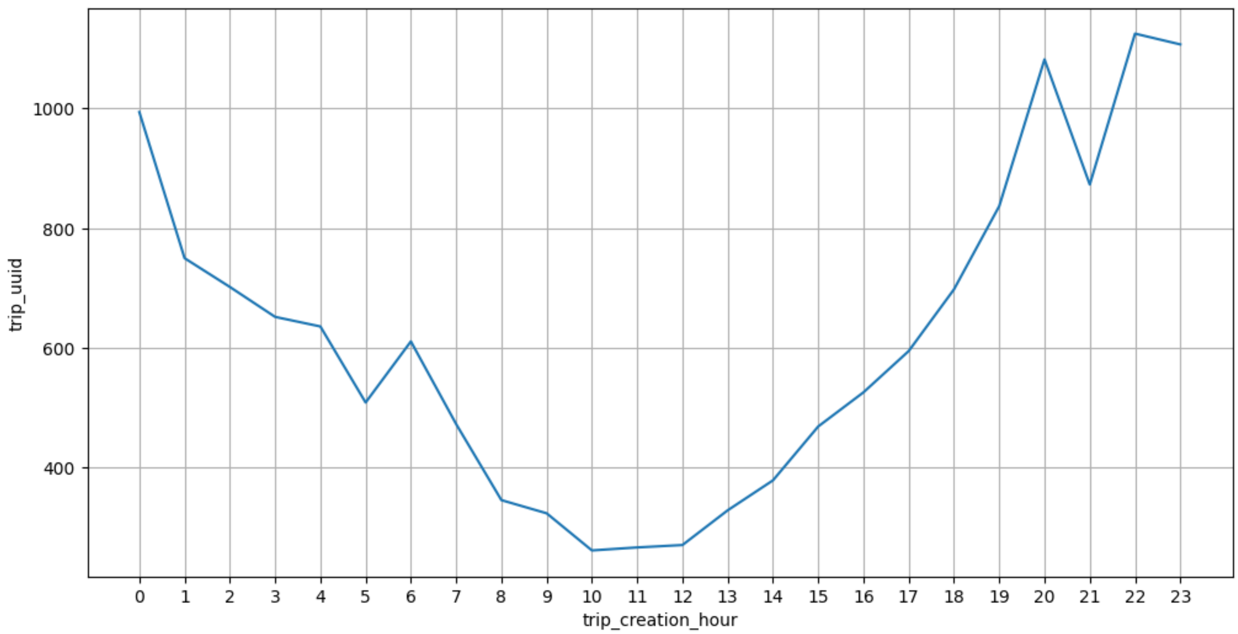
```
df_hour = df2.groupby(by = 'trip_creation_hour')
['trip_uuid'].count().to_frame().reset_index()
df_hour.head()
```

```
   trip_creation_hour  trip_uuid
0                   0        994
```

```
1                       1        750
2                       2        702
3                       3        652
4                       4        636
```

```
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()
```

```
[]
```



- the number of trips start increasing after the noon, becomes maximum at 10 P.M and then start decreasing.

```
df2['trip_creation_day'].unique()
```

```
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)
```

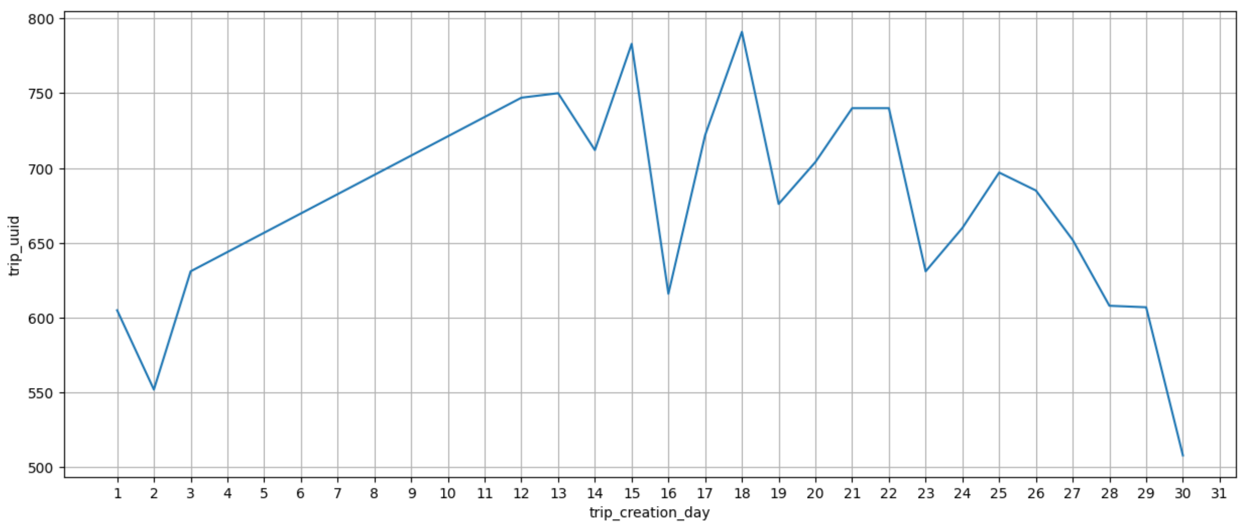
```
df_day = df2.groupby(by = 'trip_creation_day')
['trip_uuid'].count().to_frame().reset_index()
df_day.head()
```

```
   trip_creation_day  trip_uuid
0                  1        605
```

1	2	552
2	3	631
3	12	747
4	13	750

```
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()
```

```
[]
```



- 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.

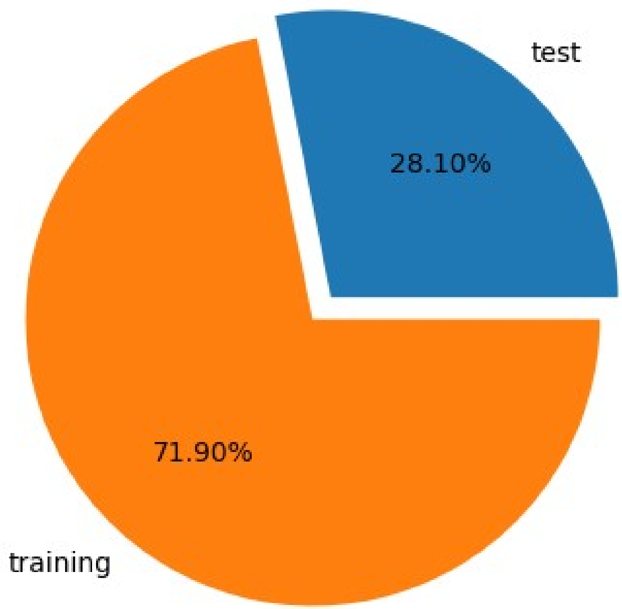
distribution of trip data for the orders

```
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()
```

	data	trip_uuid	perc
0	test	4163	28.1
1	training	10654	71.9

```
plt.pie(x = df_data['trip_uuid'],
        labels = df_data['data'],
        explode = [0, 0.1],
```

```
        autopct = '%.2f%%')
plt.plot()

[]
```



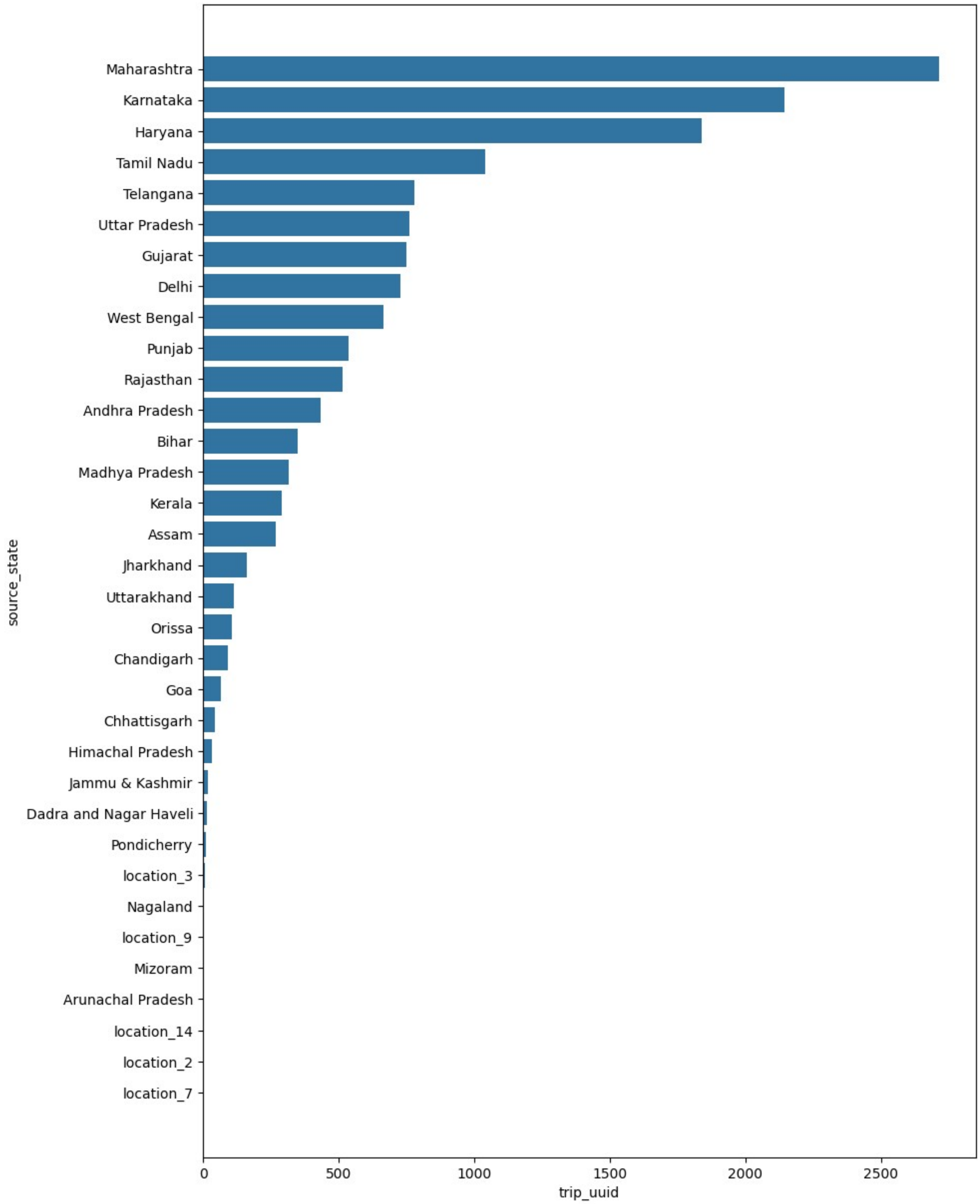
distribution of number of trips created from different states

```
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()
```

	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

```
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()
```

```
[ ]
```



Maharashtra
Karnataka
Haryana
Tamil Nadu
Telangana
Uttar Pradesh
Gujarat
Delhi
West Bengal
Punjab
Rajasthan
Andhra Pradesh
Bihar
Madhya Pradesh
Kerala
Assam
Jharkhand
Uttarakhand
Orissa
Chandigarh
Goa
Chhattisgarh
Himachal Pradesh
Jammu & Kashmir
Dadra and Nagar Haveli
Pondicherry
location_3
Nagaland
location_9
Mizoram
Arunachal Pradesh
location_14
location_2
location_7
source_state
0
500
1000
1500
2000
2500
trip_uuid

- 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

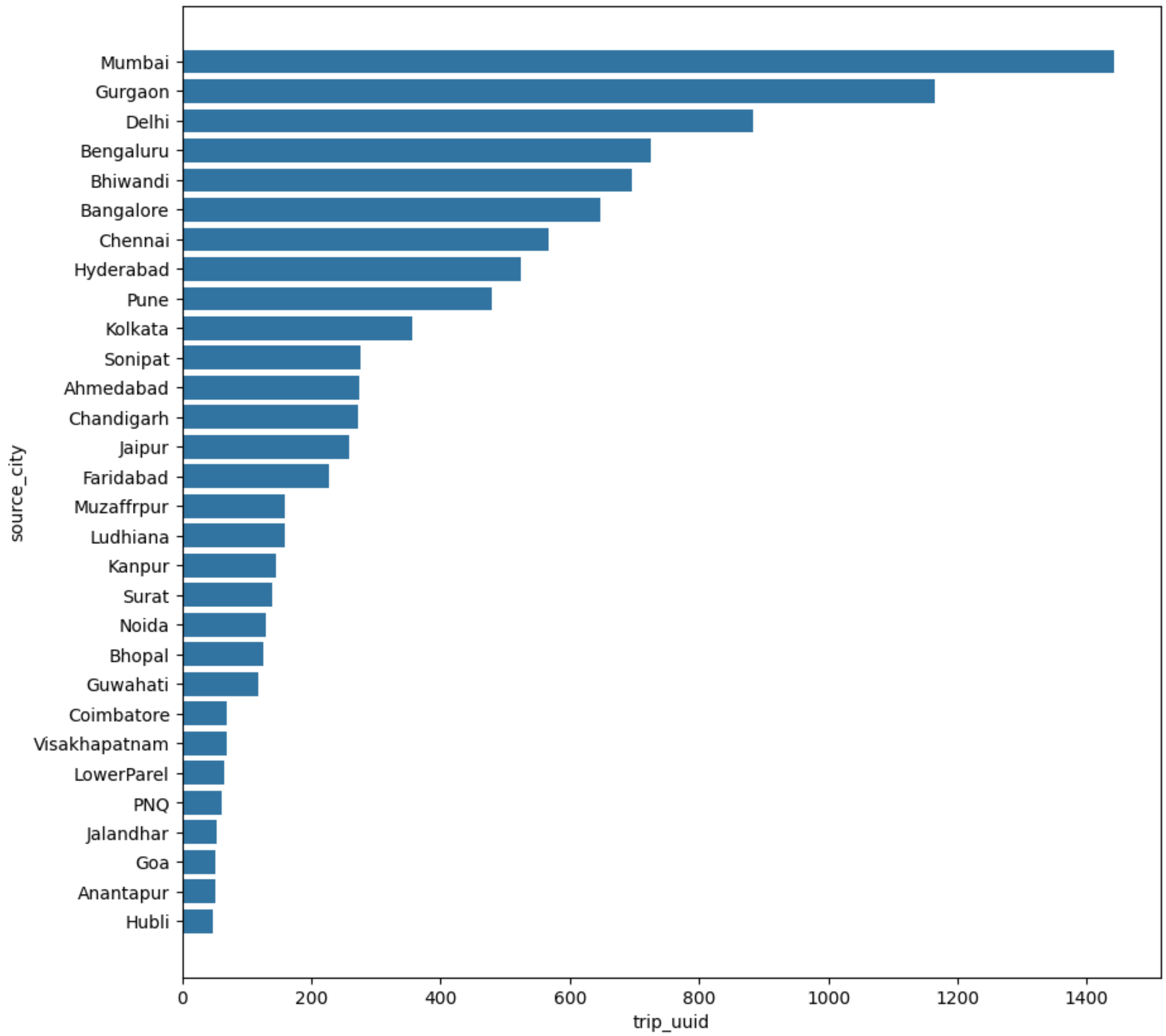
top 30 cities based on the number of trips created from different cities

```
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
```

	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

```
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()
```

```
[]
```



- 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.

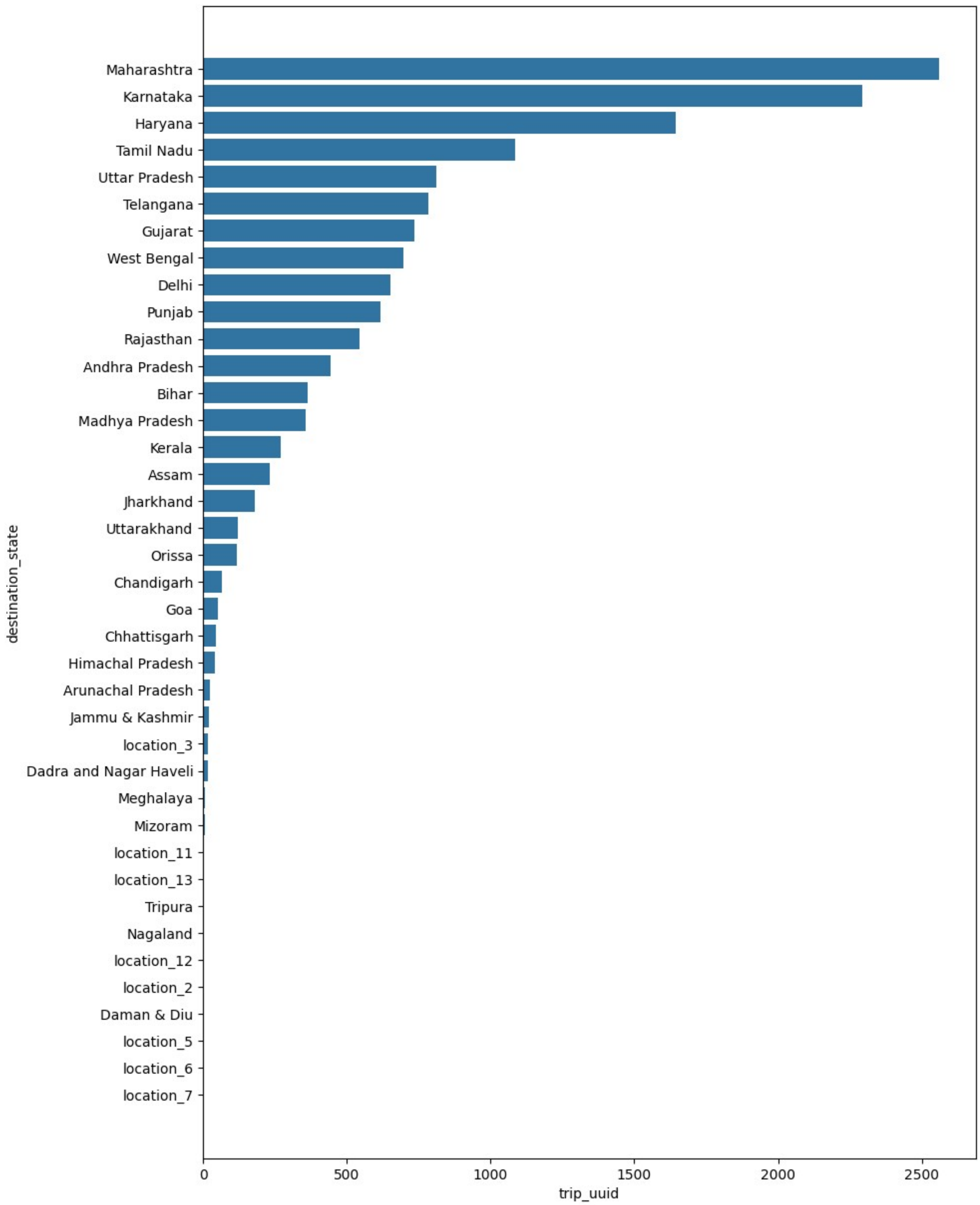
the distribution of number of trips which ended in different states

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

	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

```
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()
```

```
[]
```



- 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.

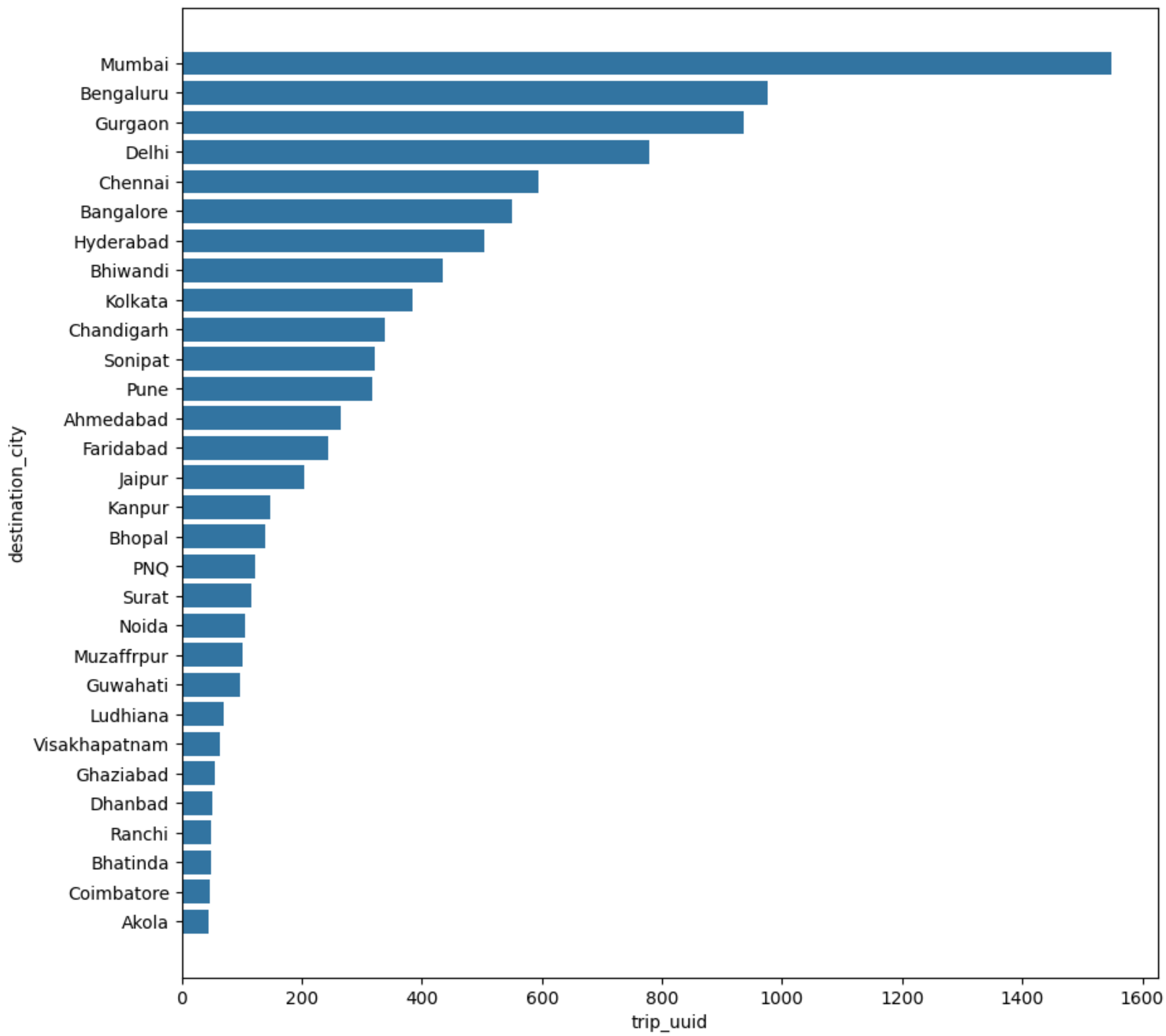
top 30 cities based on the number of trips ended in different cities

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

	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

```
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()
```

```
[]
```



- 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.

```
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']

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

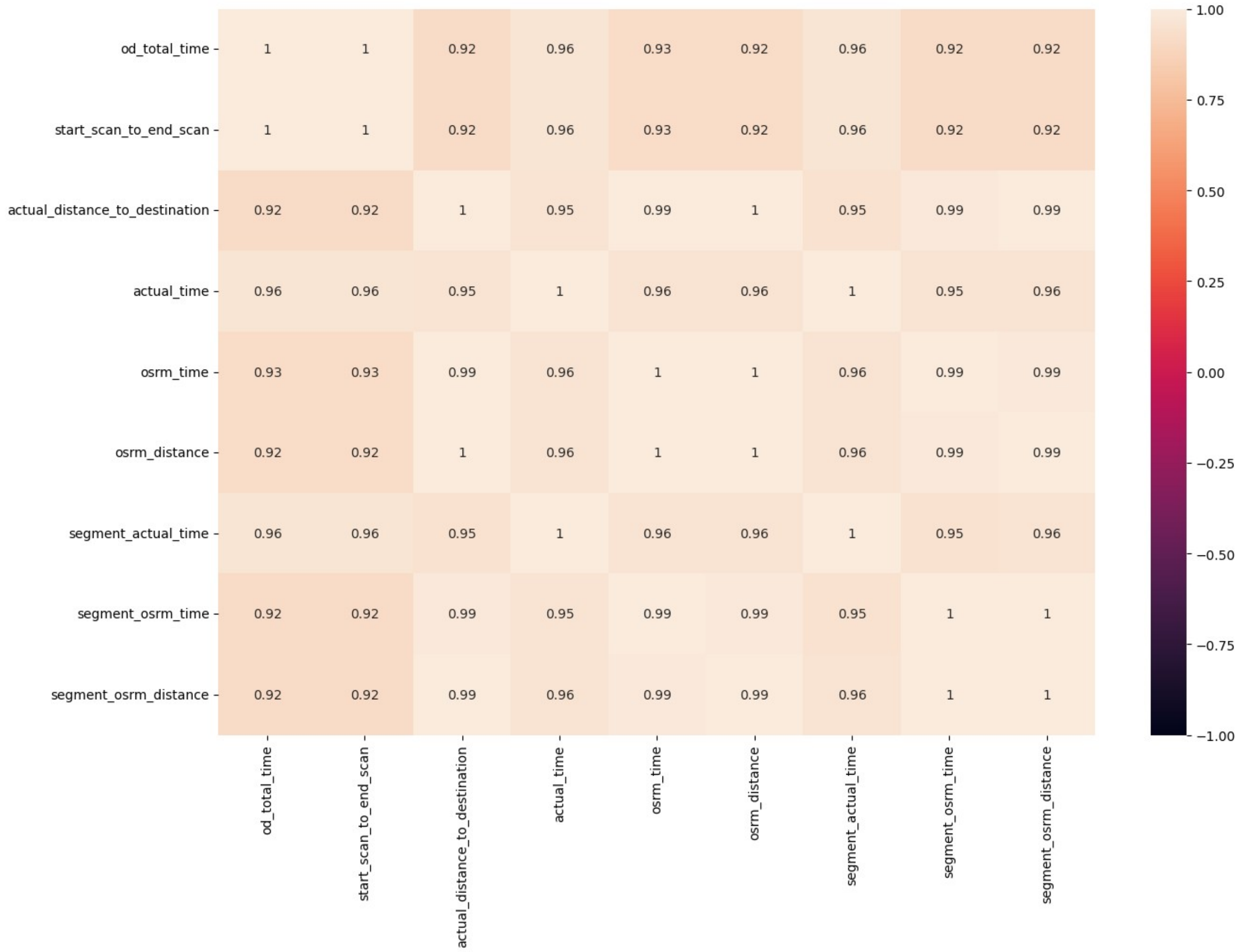
```
                                od_total_time  start_scan_to_end_scan
\
od_total_time                        1.000000                0.999999
```

```
start_scan_to_end_scan            0.999999              1.000000
actual_distance_to_destination    0.918222              0.918308
actual_time                       0.961094              0.961147
osrm_time                         0.926516              0.926571
osrm_distance                     0.924219              0.924299
segment_actual_time               0.961119              0.961171
segment_osrm_time                 0.918490              0.918561
segment_osrm_distance             0.919199              0.919291

                                actual_distance_to_destination
actual_time  \
od_total_time                                         0.918222
0.961094
start_scan_to_end_scan                                0.918308
0.961147
actual_distance_to_destination                        1.000000
0.953757
actual_time                                           0.953757
1.000000
osrm_time                                             0.993561
0.958593
osrm_distance                                         0.997264
0.959214
segment_actual_time                                   0.952821
0.999989
segment_osrm_time                                     0.987538
0.953872
segment_osrm_distance                                 0.993061
0.956967

                                osrm_time  osrm_distance
segment_actual_time  \
od_total_time                    0.926516       0.924219
0.961119
start_scan_to_end_scan           0.926571       0.924299
0.961171
actual_distance_to_destination   0.993561       0.997264
0.952821
actual_time                      0.958593       0.959214
0.999989
osrm_time                        1.000000       0.997580
0.957765
```

```
osrm_distance                          0.997580       1.000000
0.958353
segment_actual_time                    0.957765       0.958353
1.000000
segment_osrm_time                      0.993259       0.991798
0.953039
segment_osrm_distance                  0.991608       0.994710
0.956106

                                       segment_osrm_time
segment_osrm_distance
od_total_time                                   0.918490
0.919199
start_scan_to_end_scan                          0.918561
0.919291
actual_distance_to_destination                  0.987538
0.993061
actual_time                                     0.953872
0.956967
osrm_time                                       0.993259
0.991608
osrm_distance                                   0.991798
0.994710
segment_actual_time                             0.953039
0.956106
segment_osrm_time                               1.000000
0.996092
segment_osrm_distance                           0.996092
1.000000
```

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

```
[]
```



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

3. In-depth analysis and feature engineering:

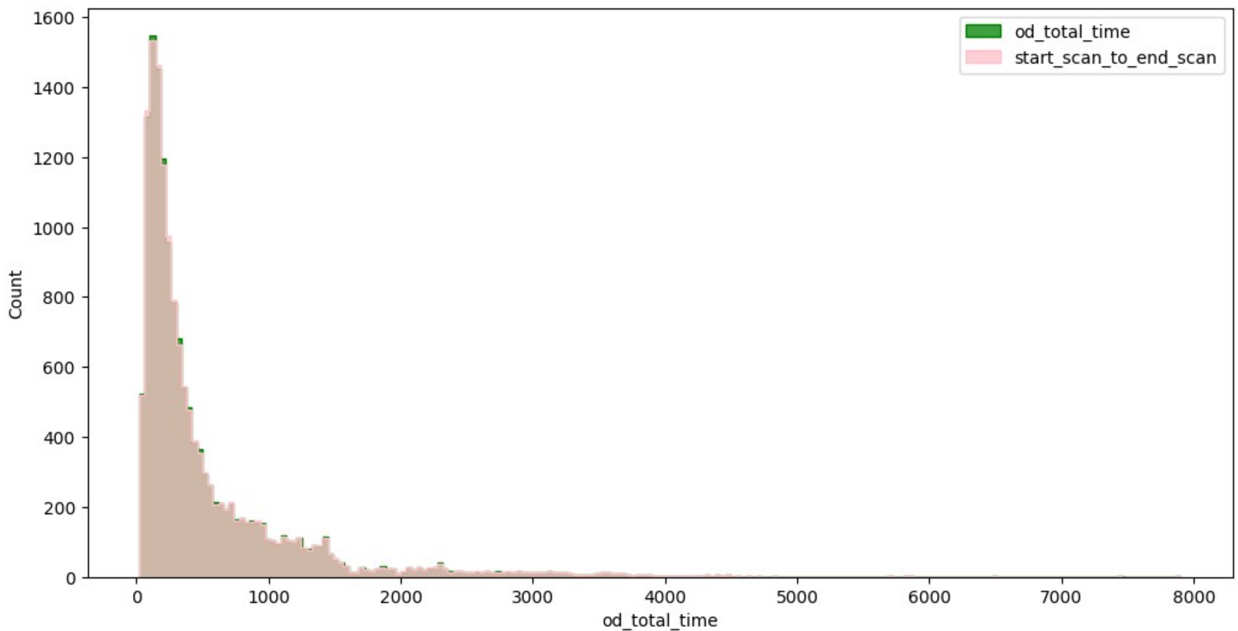
Compare the difference between od_total_time and start_scan_to_end_scan. Do hypothesis testing/ Visual analysis to check.

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

	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

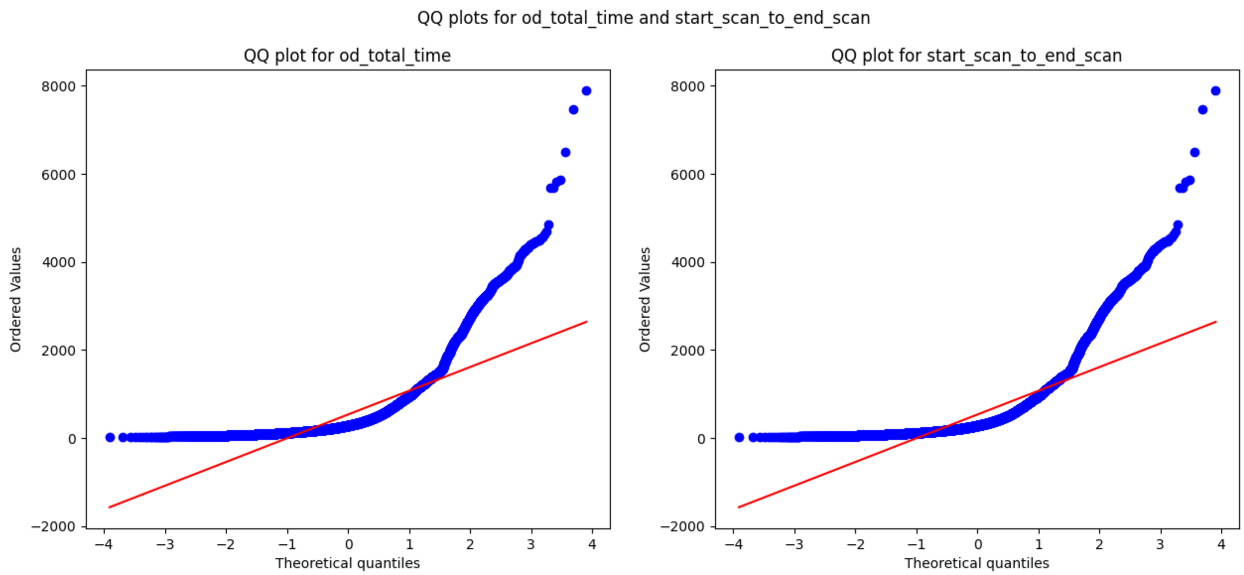
- Visual Tests to know if the samples follow normal distribution

```
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()

[]
```



- Distribution check using **QQ Plot**

```
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()

[]
```



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

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**

```
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

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.

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

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

/usr/local/lib/python3.10/dist-packages/scipy/stats/
_morestats.py:1882: UserWarning: p-value may not be accurate for N >
5000.
  warnings.warn("p-value may not be accurate for N > 5000.")

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

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

- 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**

```
# 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.

```
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
```

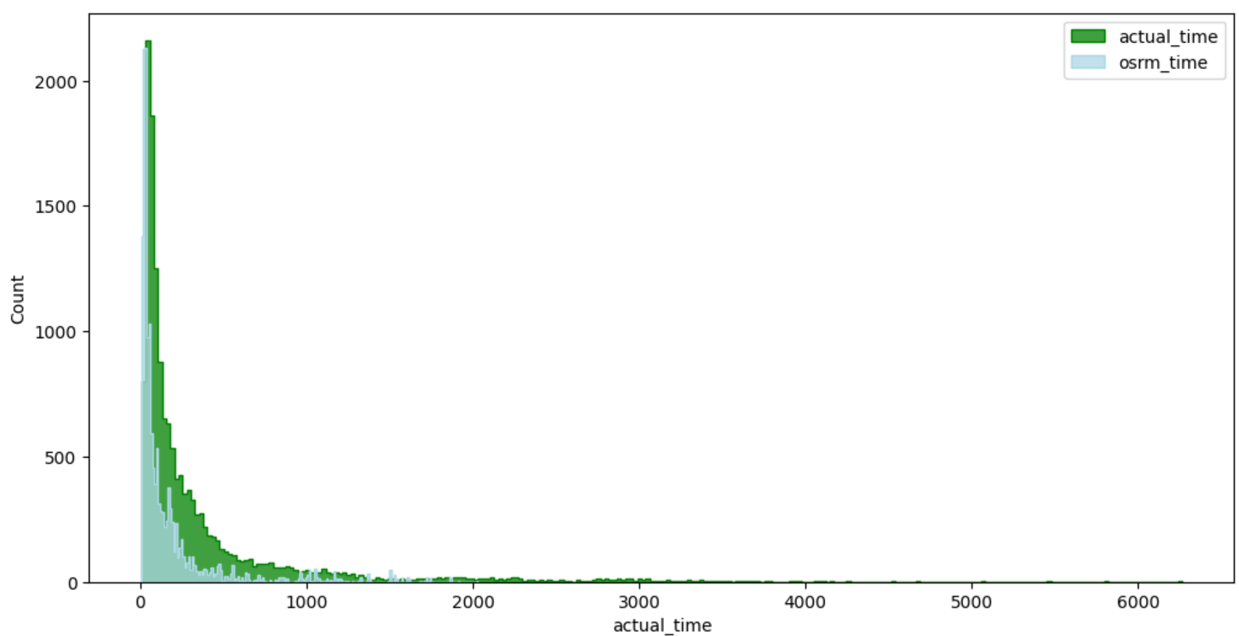
Since p-value > alpha therfore it can be concluded that od_total_time and start_scan_to_end_scan are similar.

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

	actual_time	osrm_time
count	14817.000000	14817.000000
mean	357.143768	161.384018
std	561.396118	271.360992
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

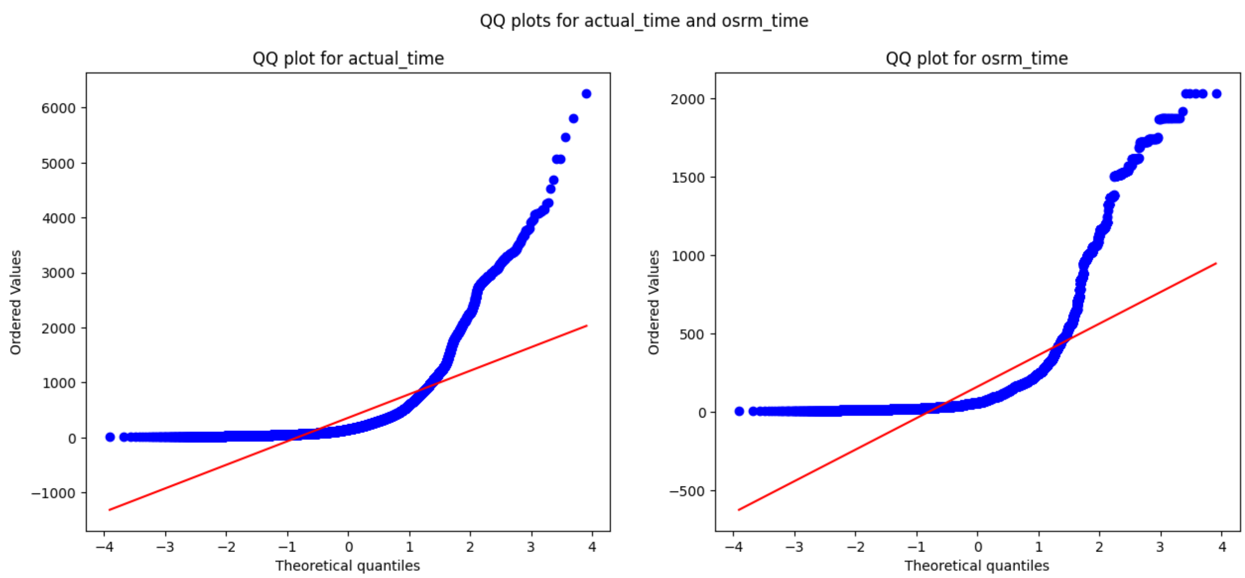
```
plt.figure(figsize = (12, 6))
sns.histplot(df2['actual_time'], element = 'step', color = 'green')
sns.histplot(df2['osrm_time'], element = 'step', color = 'lightblue')
plt.legend(['actual_time', 'osrm_time'])
plt.plot()

[]
```



- Distribution check using **QQ Plot**

```
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()
```

```
[]
```



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

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**

```
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
```

```
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.

```
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 1.020620453603145e-28
The sample does not follow normal distribution

/usr/local/lib/python3.10/dist-packages/scipy/stats/
_morestats.py:1882: UserWarning: p-value may not be accurate for N >
5000.
  warnings.warn("p-value may not be accurate for N > 5000.")

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 3.5882550510138333e-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**

```
# 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.

```
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)

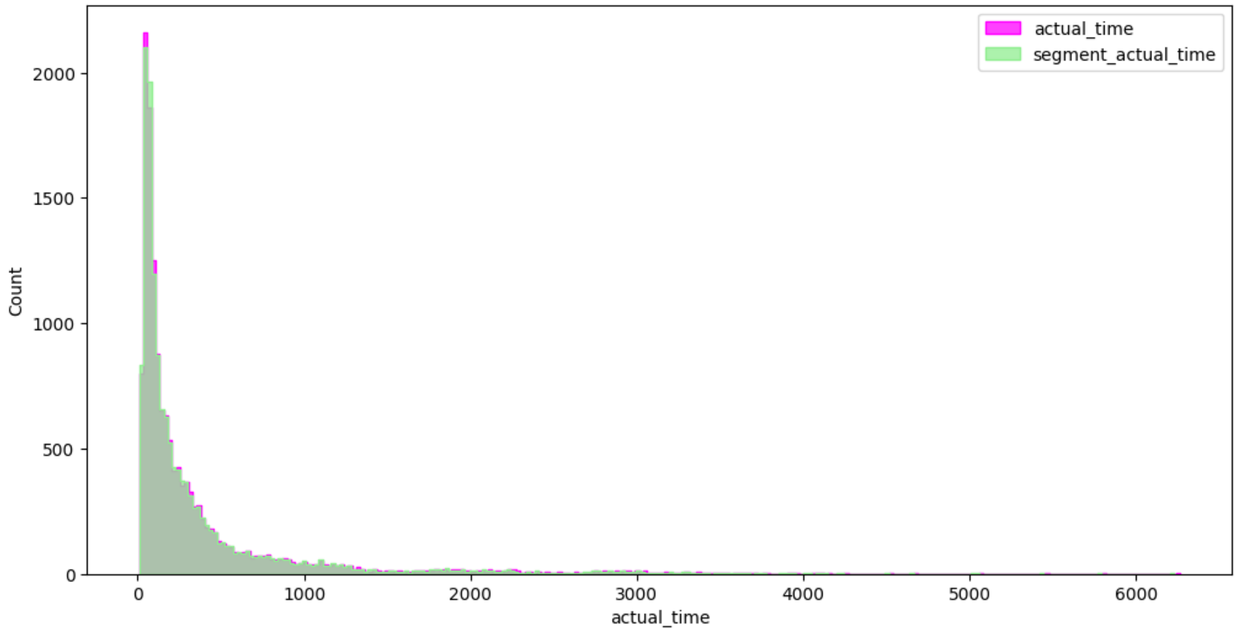
```
df2[['actual_time', 'segment_actual_time']].describe()
```

	actual_time	segment_actual_time
count	14817.000000	14817.000000
mean	357.143768	353.892273
std	561.396118	556.247925
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

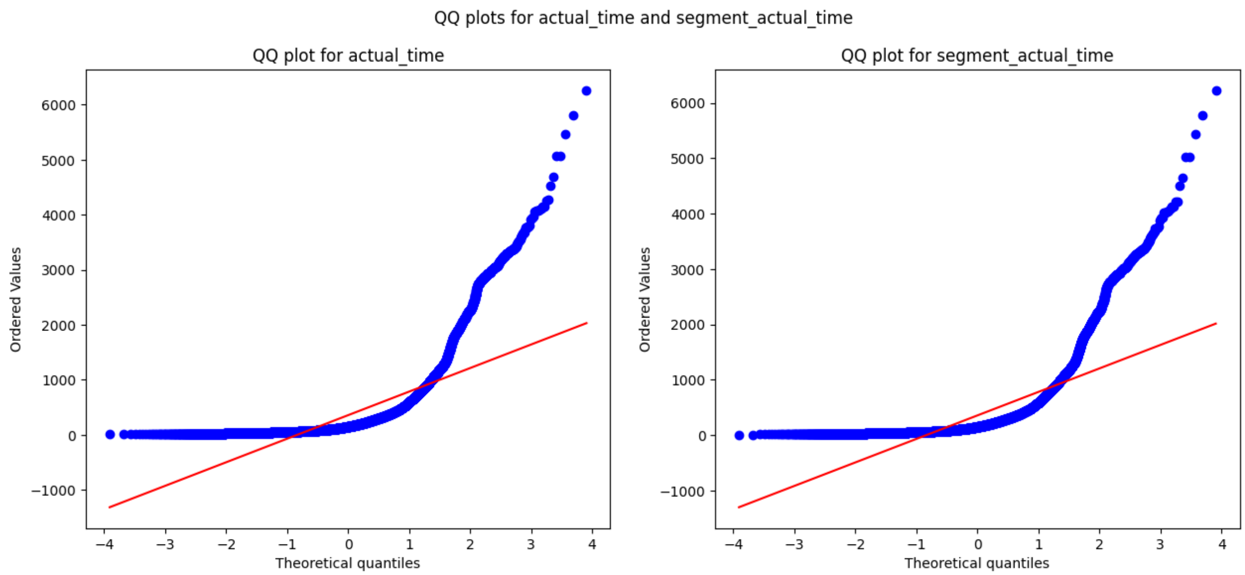
```
plt.figure(figsize = (12, 6))
sns.histplot(df2['actual_time'], element = 'step', color = 'magenta')
sns.histplot(df2['segment_actual_time'], element = 'step', color =
'lightgreen')
plt.legend(['actual_time', 'segment_actual_time'])
plt.plot()
```

```
[]
```



- Distribution check using **QQ Plot**

```
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()

[]
```



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

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**

```
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

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.

```
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 1.020620453603145e-28
The sample does not follow normal distribution

/usr/local/lib/python3.10/dist-packages/scipy/stats/
_morestats.py:1882: UserWarning: p-value may not be accurate for N >
5000.
  warnings.warn("p-value may not be accurate for N > 5000.")

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 5.700074948787037e-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**

```
# 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.

```
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)

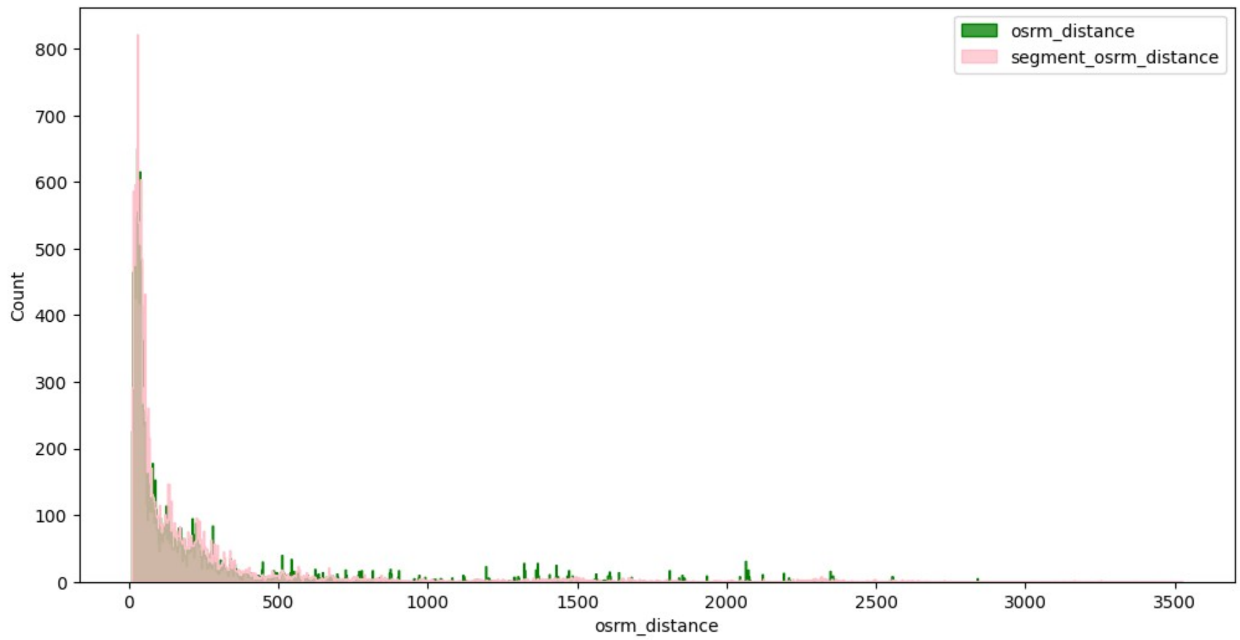
```
df2[['osrm_distance', 'segment_osrm_distance']].describe()
```

	osrm_distance	segment_osrm_distance
count	14817.000000	14817.000000
mean	204.344711	223.201157
std	370.395569	416.628387
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

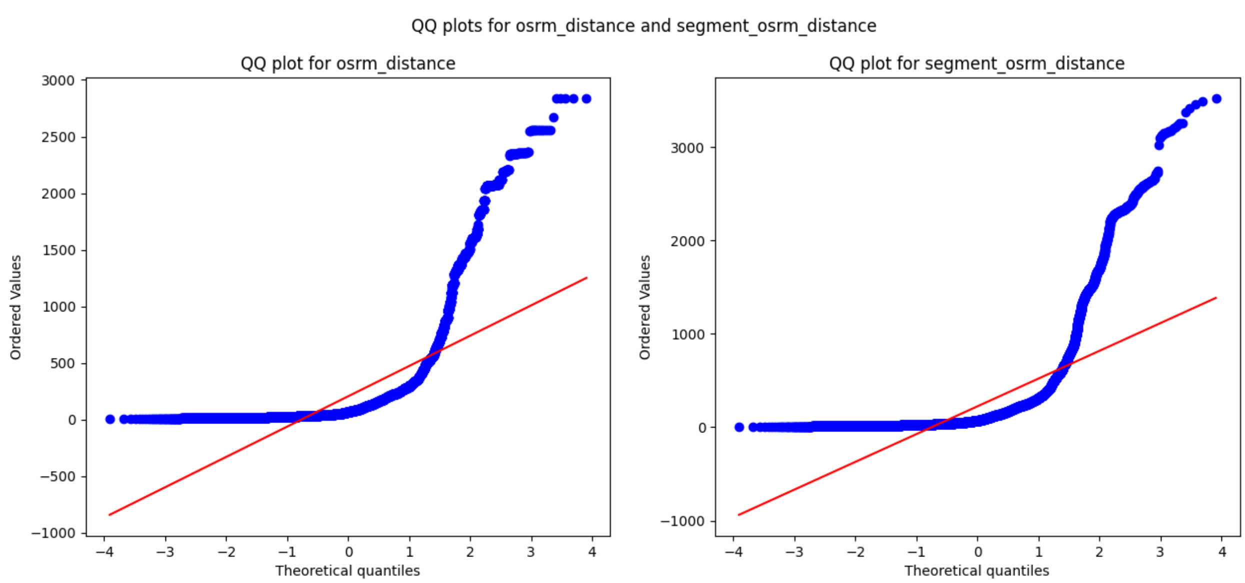
```
plt.figure(figsize = (12, 6))
sns.histplot(df2['osrm_distance'], element = 'step', color = 'green',
bins = 1000)
sns.histplot(df2['segment_osrm_distance'], element = 'step', color =
'pink', bins = 1000)
plt.legend(['osrm_distance', 'segment_osrm_distance'])
plt.plot()
```

```
[]
```



- Distribution check using **QQ Plot**

```
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()

[]
```



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

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**

```
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
```

```
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.

```
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 7.063104779582808e-41
The sample does not follow normal distribution

/usr/local/lib/python3.10/dist-packages/scipy/stats/
_morestats.py:1882: UserWarning: p-value may not be accurate for N >
5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

```
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 3.049169406432229e-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**

```
# 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.

```
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 9.509410818847664e-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)

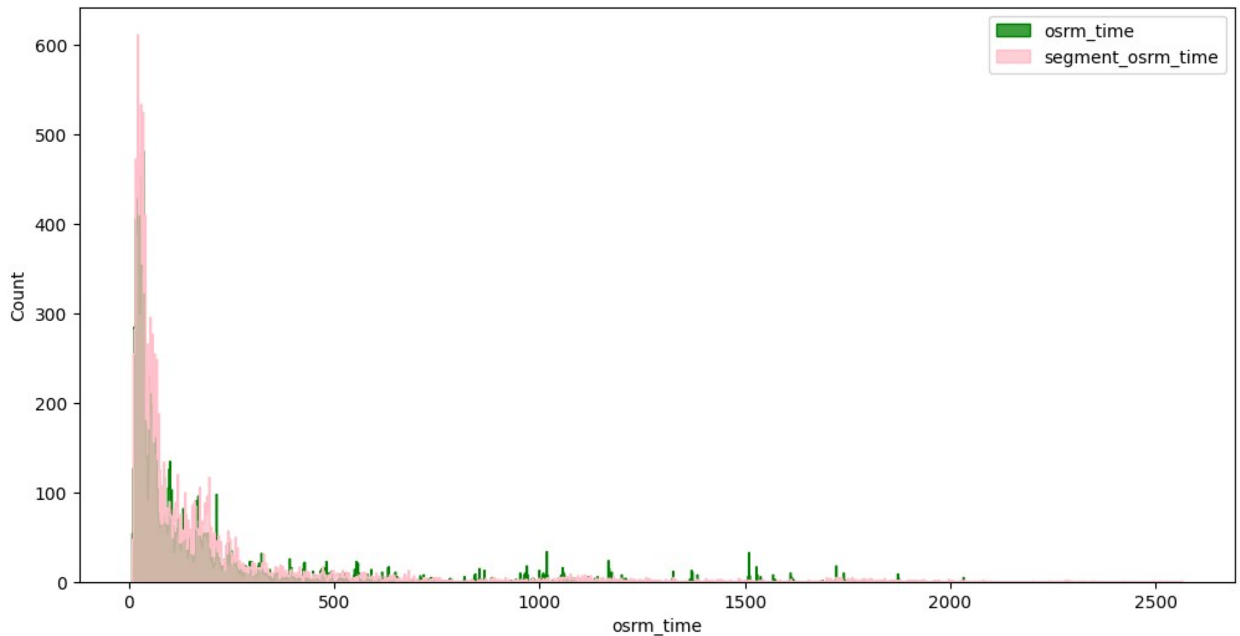
```
df2[['osrm_time', 'segment_osrm_time']].describe().T
```

```
                     count        mean         std  min   25%   50%  
75%  \
osrm_time          14817.0  161.384018  271.360992  6.0  29.0  60.0  
168.0   
segment_osrm_time  14817.0  180.949783  314.542053  6.0  31.0  65.0  
185.0   

                      max  
osrm_time          2032.0  
segment_osrm_time  2564.0  
```

- Visual Tests to know if the samples follow normal distribution

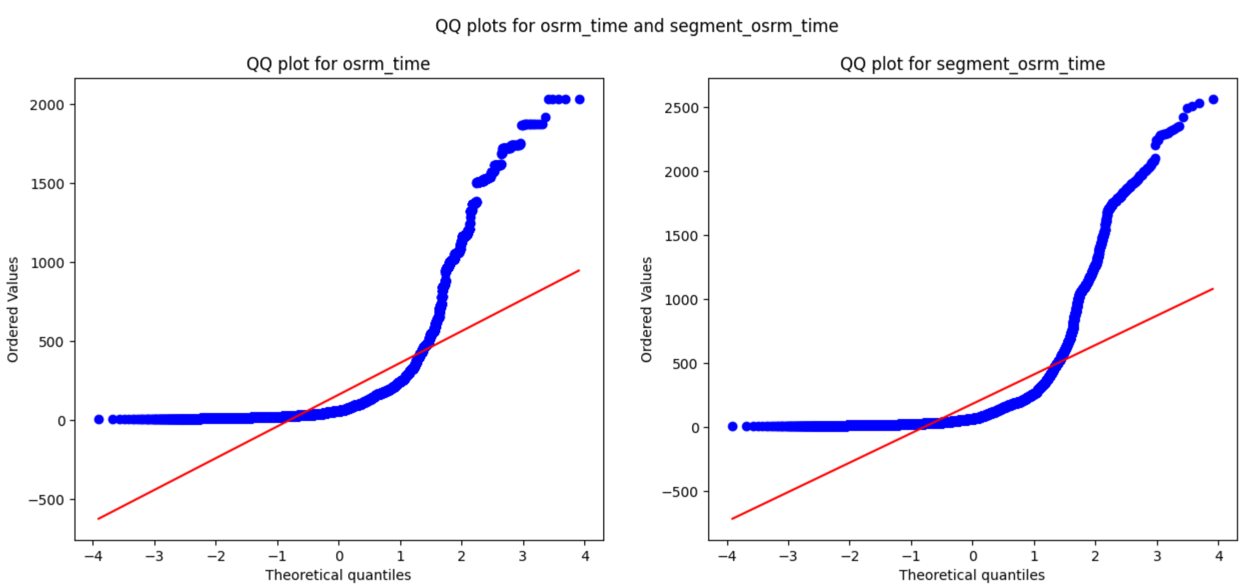
```
plt.figure(figsize = (12, 6))
sns.histplot(df2['osrm_time'], element = 'step', color = 'green', bins
= 1000)
sns.histplot(df2['segment_osrm_time'], element = 'step', color =
'pink', bins = 1000)
plt.legend(['osrm_time', 'segment_osrm_time'])
plt.plot()
```

```
[]
```



- Distribution check using **QQ Plot**

```
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()

[]
```



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

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**

```
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

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.

```
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 3.5882550510138333e-35
The sample does not follow normal distribution

/usr/local/lib/python3.10/dist-packages/scipy/stats/
_morestats.py:1882: UserWarning: p-value may not be accurate for N > 
5000.
  warnings.warn("p-value may not be accurate for N > 5000.")

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 4.943039152219146e-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**

```
# 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.

```
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

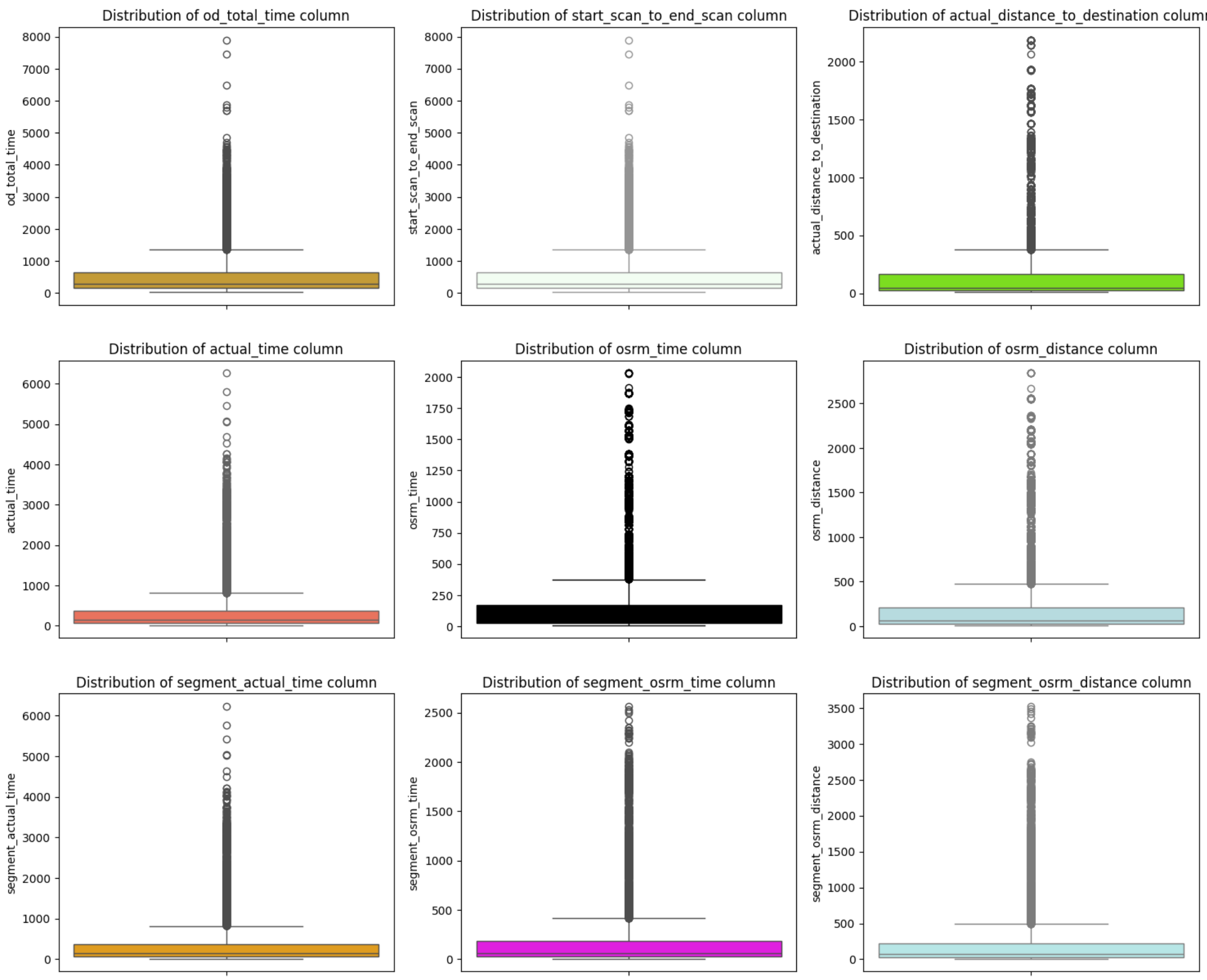
```
numerical_columns = ['od_total_time', 'start_scan_to_end_scan',
'actual_distance_to_destination',
```

```
                    'actual_time', 'osrm_time', 'osrm_distance',
'segment_actual_time',
                    'segment_osrm_time', 'segment_osrm_distance']
df2[numerical_columns].describe().T
```

```
                                   count        mean         std
min  \
od_total_time                    14817.0  531.697630  658.868223
23.460000
start_scan_to_end_scan           14817.0  530.810016  658.705957
23.000000
actual_distance_to_destination   14817.0  164.477829  305.388153
9.002461
actual_time                      14817.0  357.143768  561.396118
9.000000
osrm_time                        14817.0  161.384018  271.360992
6.000000
osrm_distance                    14817.0  204.344711  370.395569
9.072900
segment_actual_time              14817.0  353.892273  556.247925
9.000000
segment_osrm_time                14817.0  180.949783  314.542053
6.000000
segment_osrm_distance            14817.0  223.201157  416.628387
9.072900

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

                                         max
od_total_time                    7898.550000
start_scan_to_end_scan           7898.000000
actual_distance_to_destination   2186.531738
actual_time                      6265.000000
osrm_time                        2032.000000
osrm_distance                    2840.081055
segment_actual_time              6230.000000
segment_osrm_time                2564.000000
segment_osrm_distance            3523.632324
```

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

```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.

```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)

```
# Get value counts before one-hot encoding

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

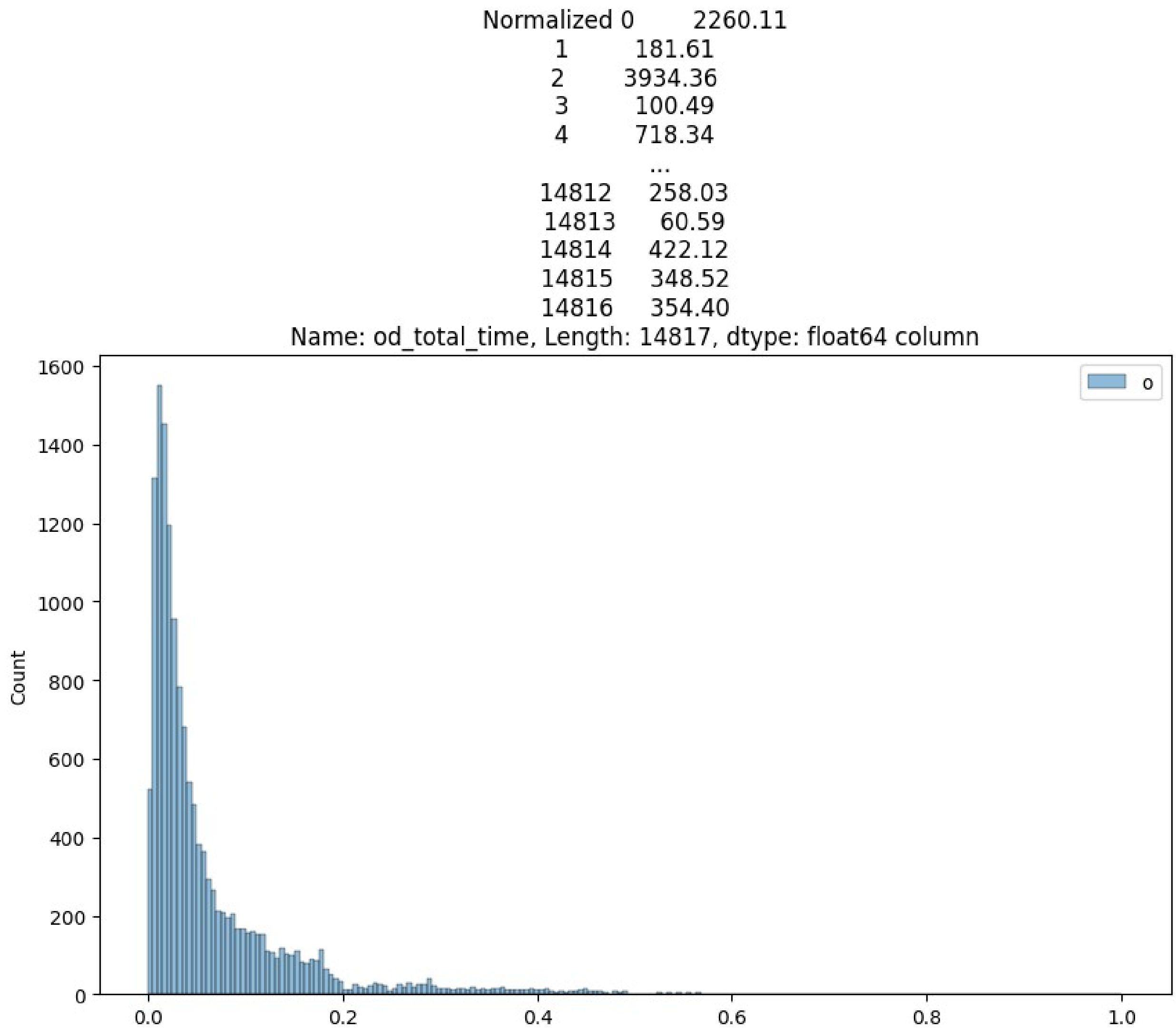
```
Carting    8908
FTL        5909
Name: route_type, dtype: int64
```

```
# Perform one-hot encoding on categorical column route type

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

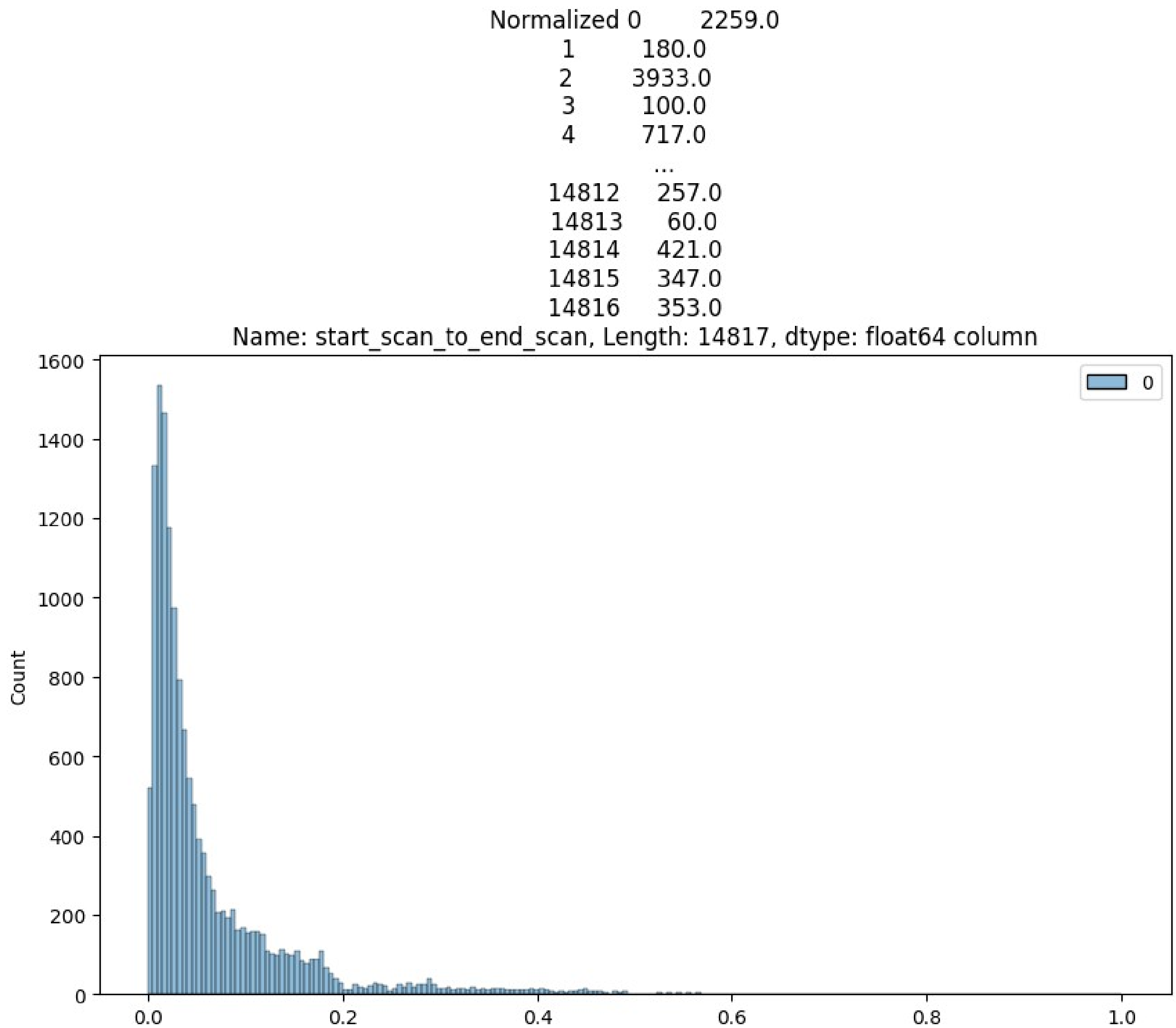
```
# Get value counts after one-hot encoding

df2['route_type'].value_counts()

0    8908
1    5909
Name: route_type, dtype: int64

# Get value counts of categorical variable 'data' before one-hot
encoding

df2['data'].value_counts()

training    10654
test         4163
Name: data, dtype: int64

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

label_encoder = LabelEncoder()
df2['data'] = label_encoder.fit_transform(df2['data'])

# Get value counts after one-hot encoding

df2['data'].value_counts()

1    10654
0     4163
Name: data, dtype: int64
```

Normalize/ Standardize the numerical features using MinMaxScaler or StandardScaler.

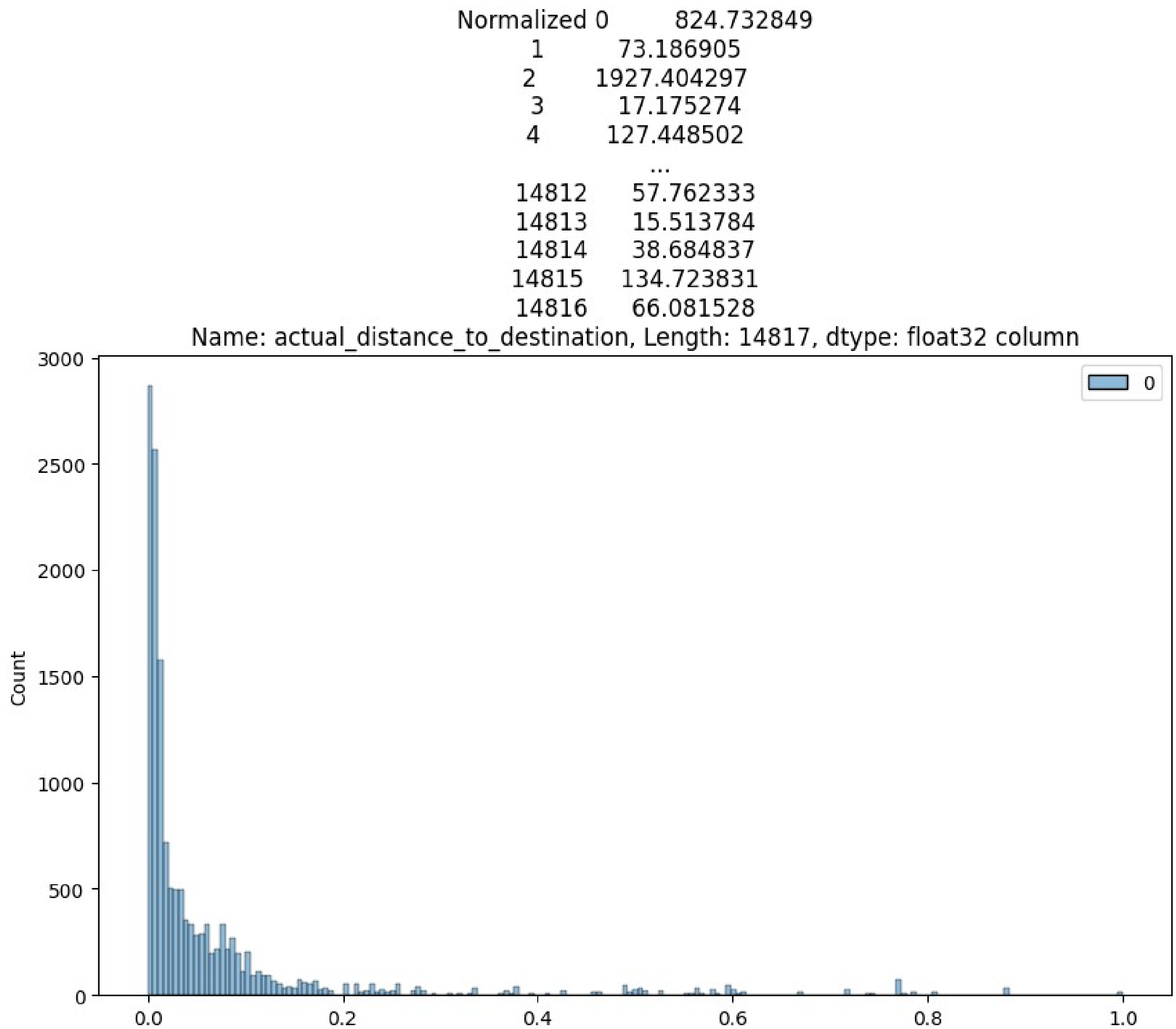
```
from sklearn.preprocessing import MinMaxScaler

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()

[]
```




```
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()

[]
```

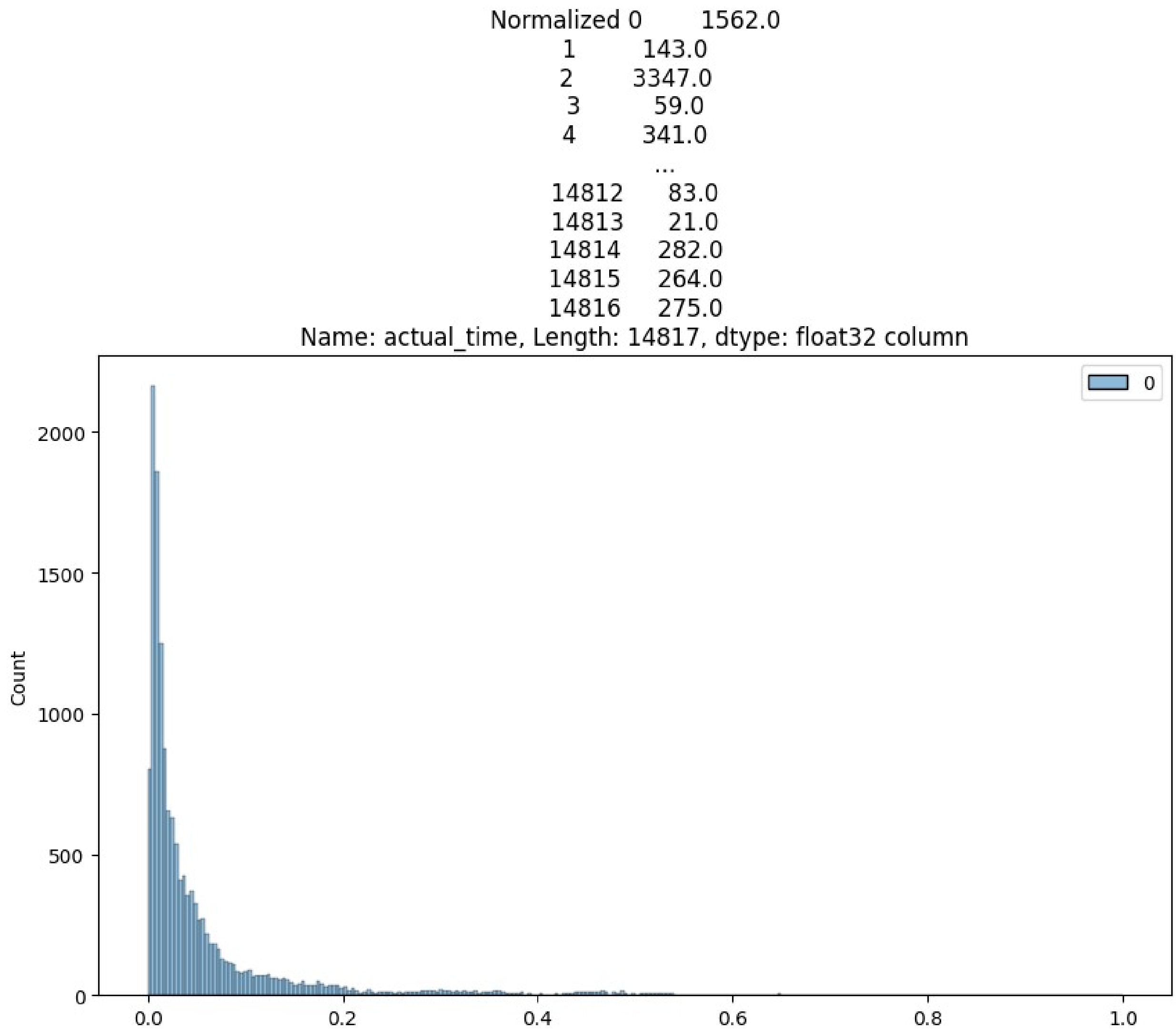



```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled =
scaler.fit_transform(df2['actual_distance_to_destination'].to_numpy().
reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['actual_distance_to_destination']}
column")
plt.plot()

[]
```

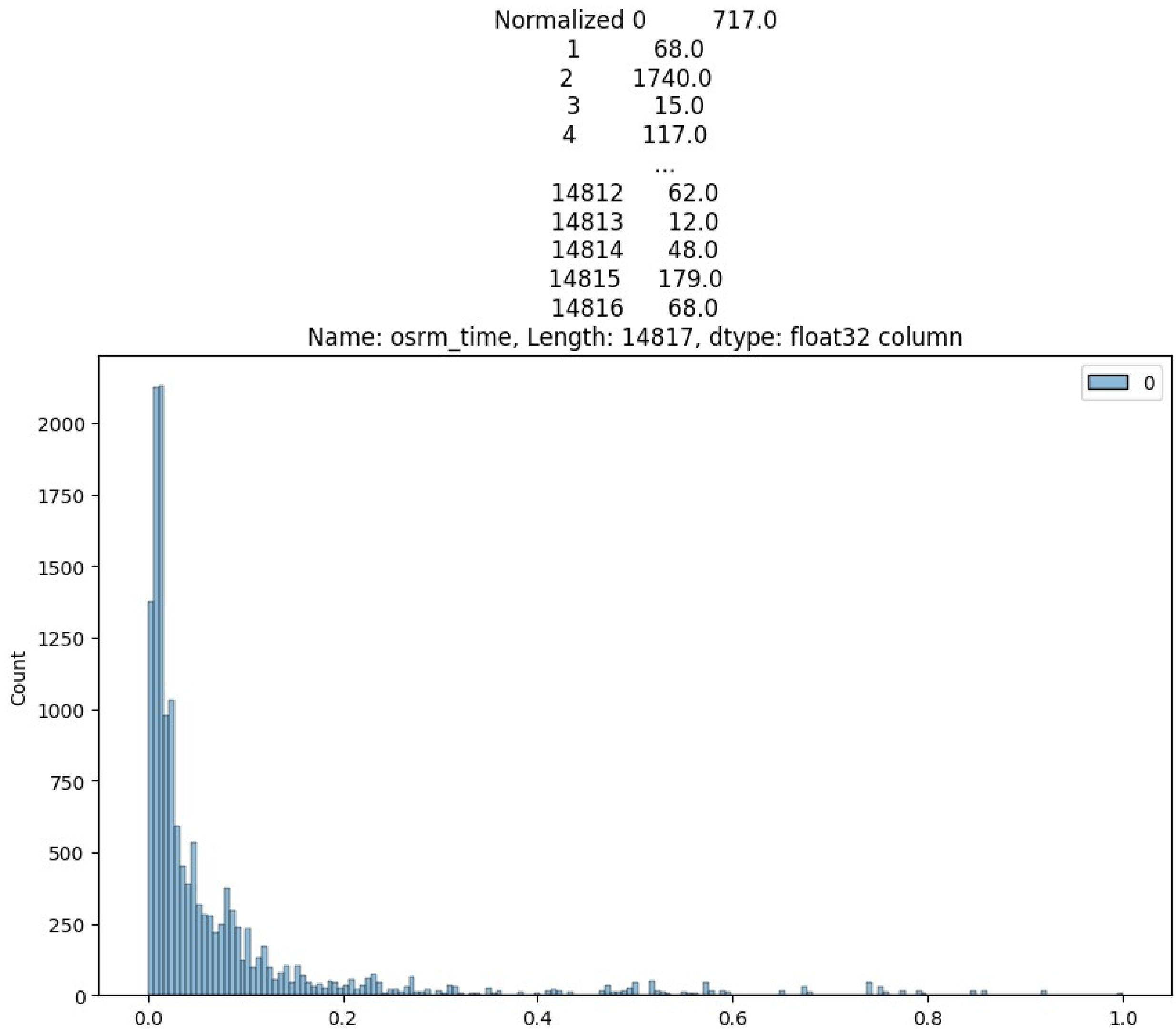



```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['actual_time'].to_numpy().reshape(-
1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['actual_time']} column")
plt.plot()
```

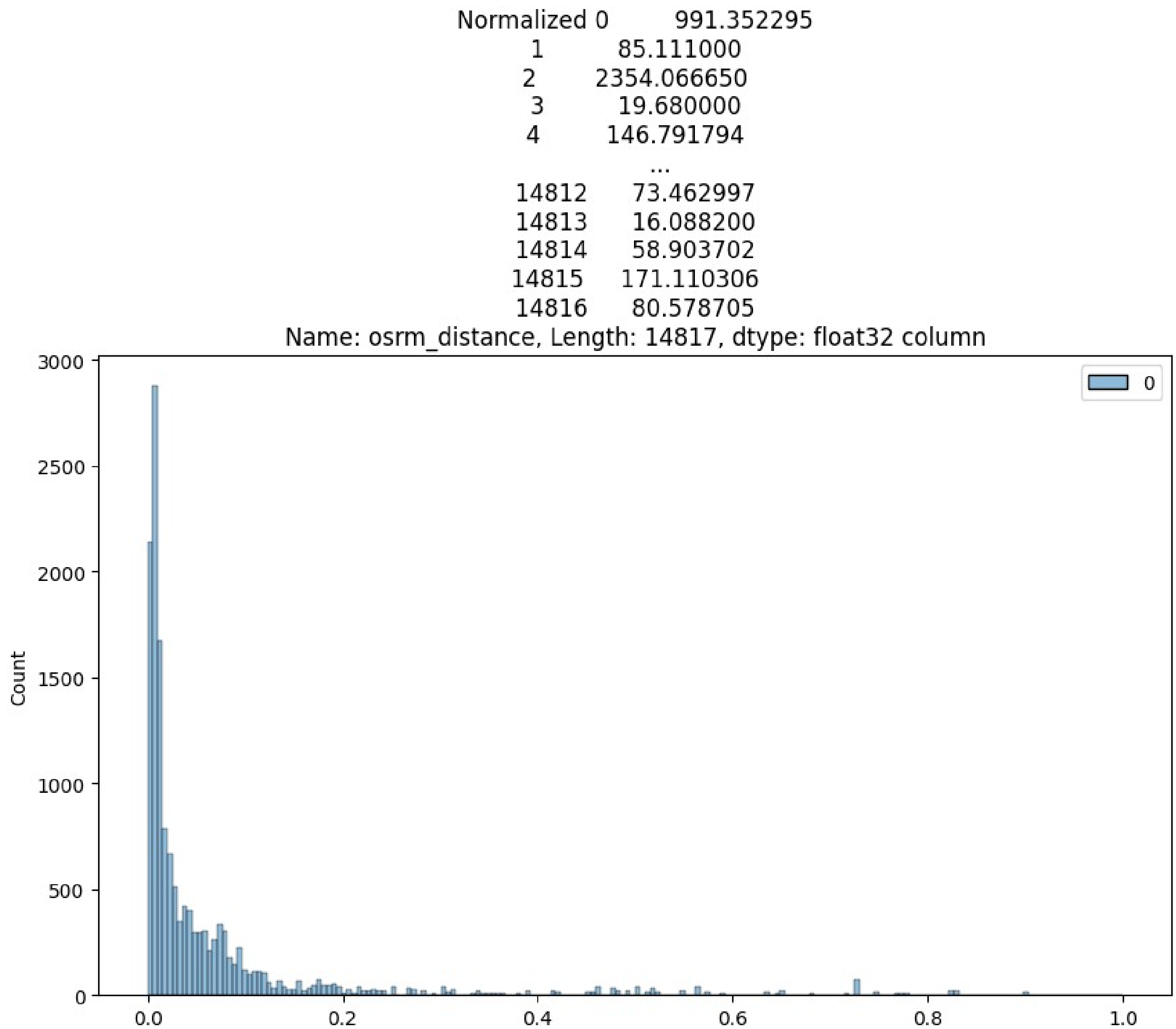
```
[]
```




```
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()

[]
```

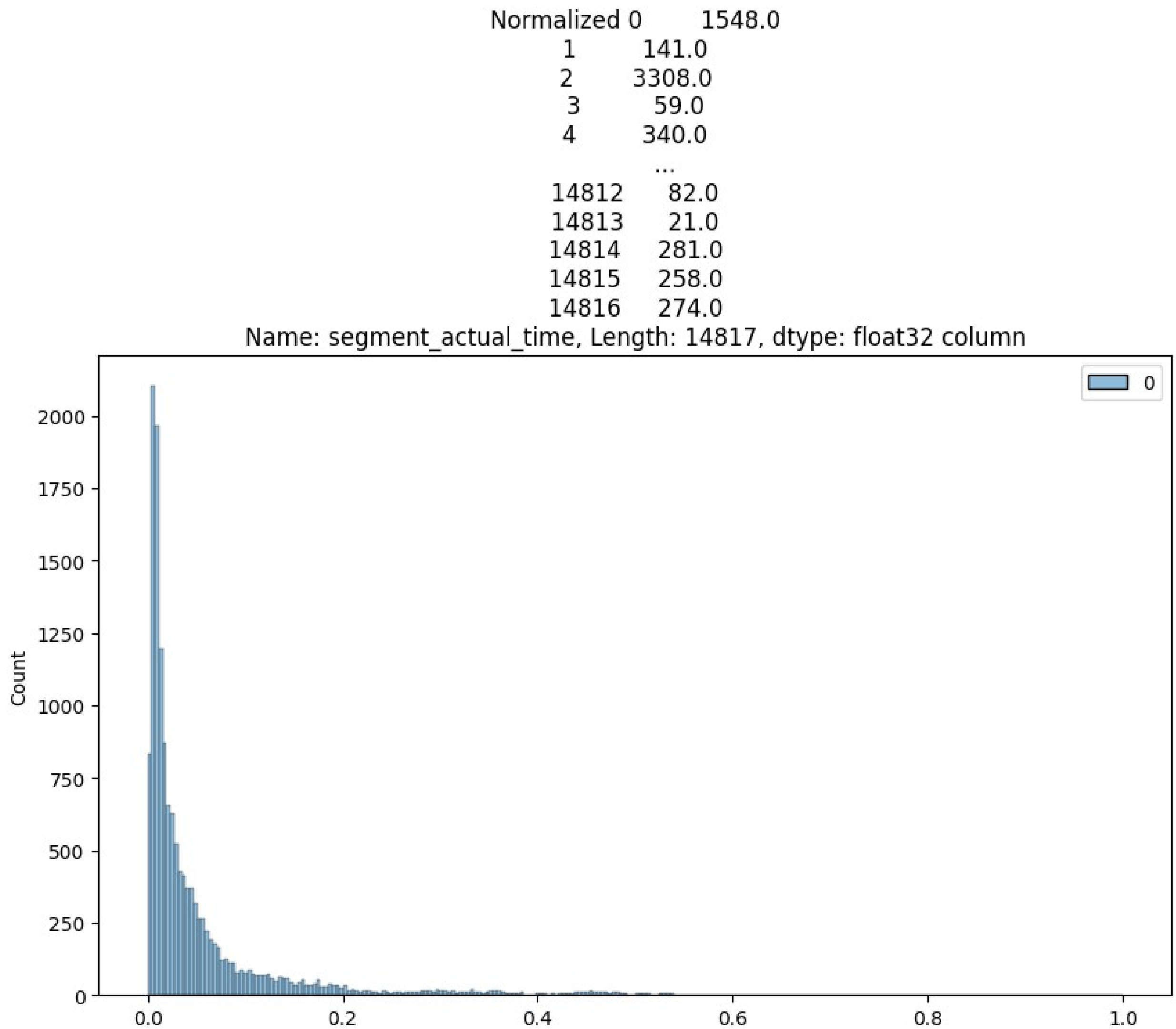



```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled =
scaler.fit_transform(df2['osrm_distance'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['osrm_distance']} column")
plt.plot()

[]
```

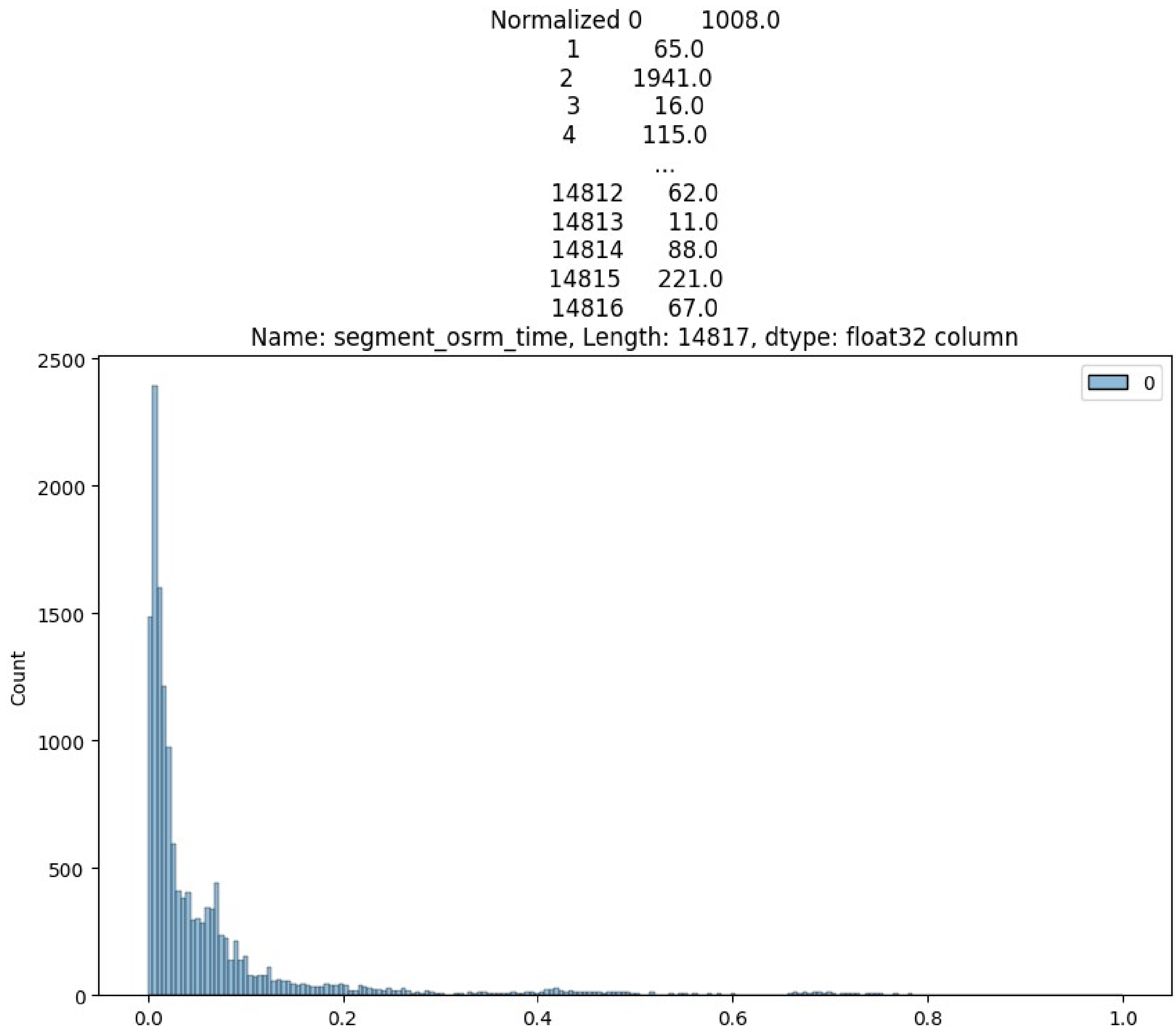



```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled =
scaler.fit_transform(df2['segment_actual_time'].to_numpy().reshape(-1,
1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['segment_actual_time']} column")
plt.plot()
```

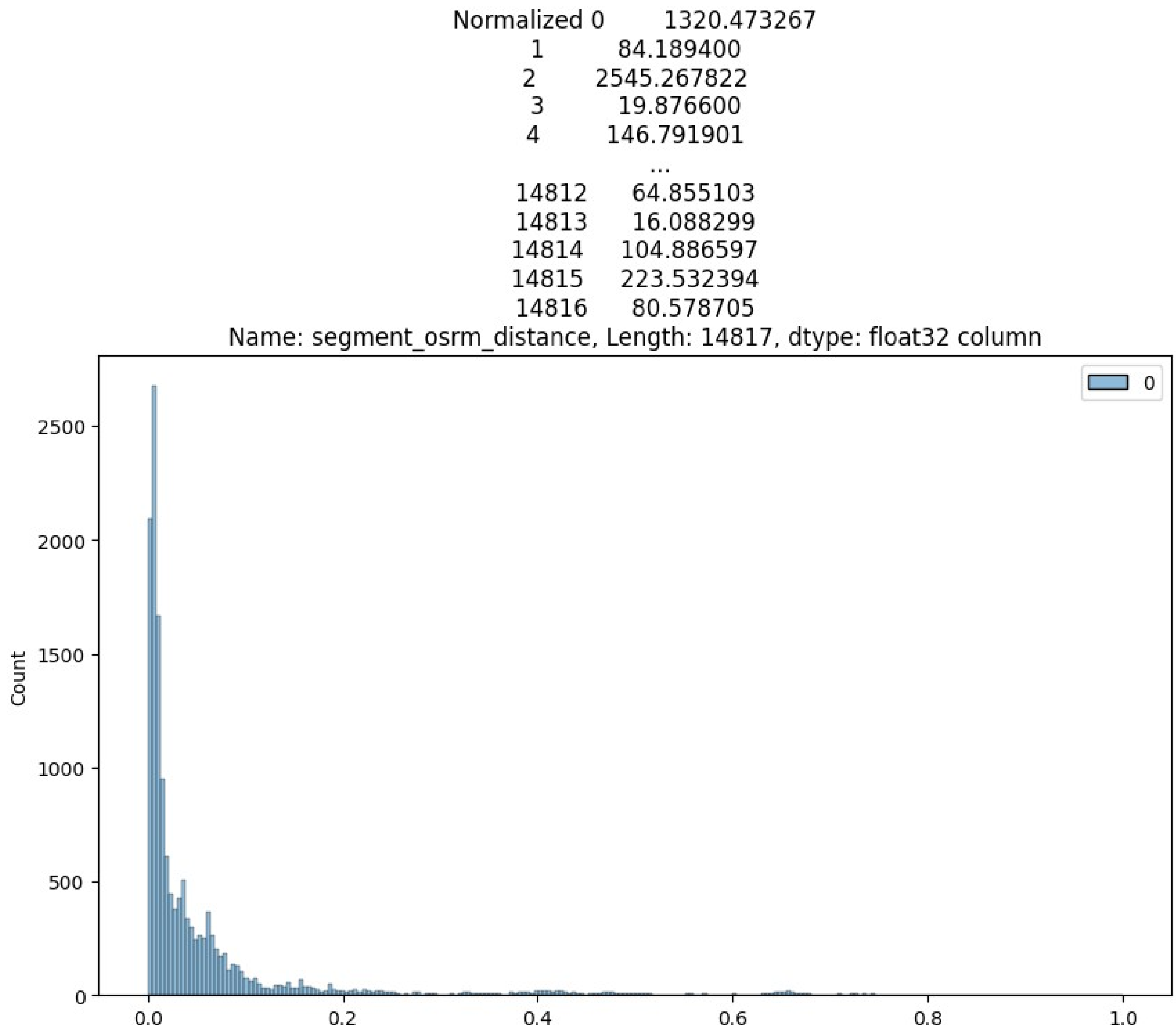
```
[]
```




```
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()

[]
```

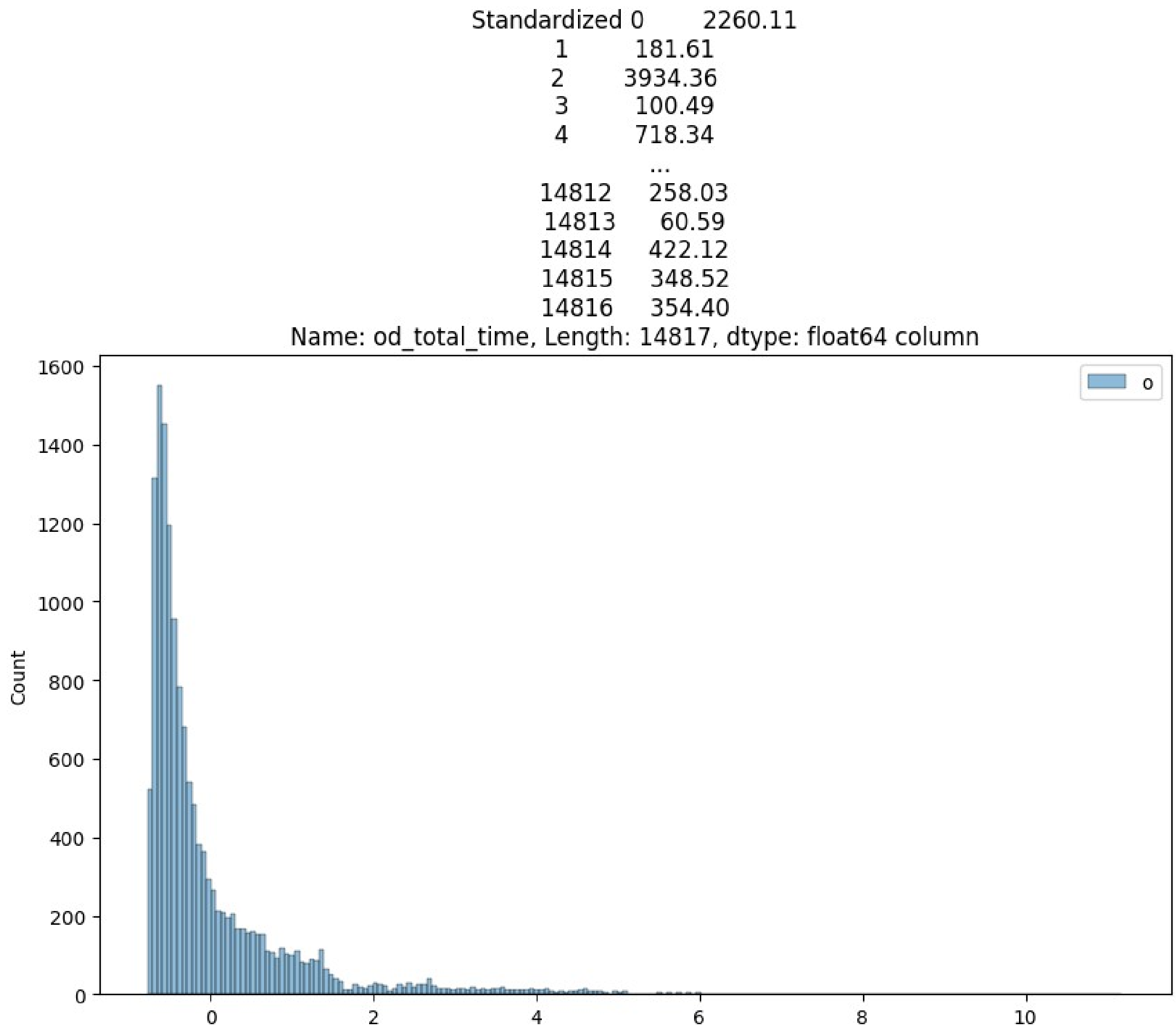



```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled =
scaler.fit_transform(df2['segment_osrm_distance'].to_numpy().reshape(-
1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['segment_osrm_distance']} column")
plt.plot()

[]
```

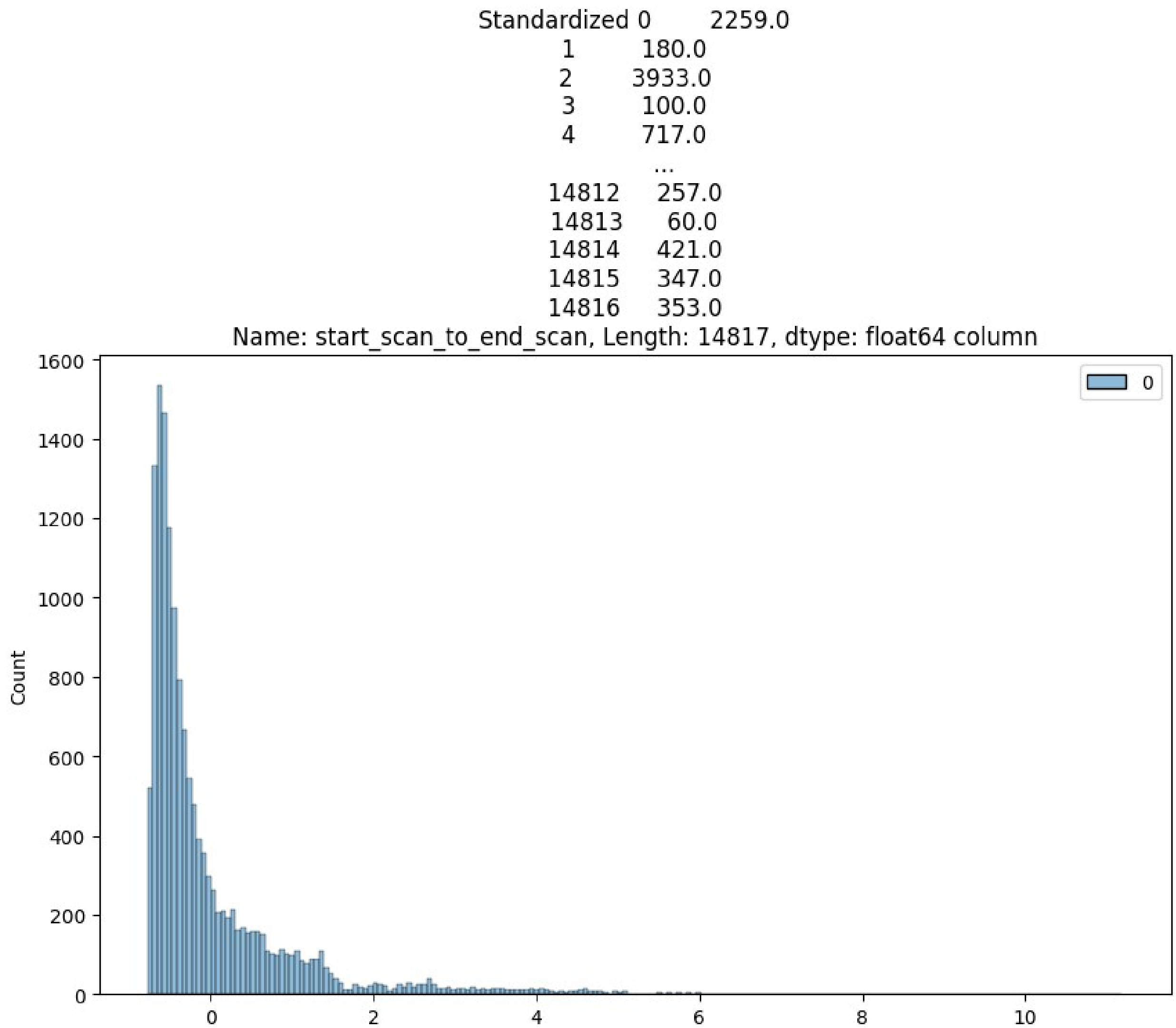


Column Standardization

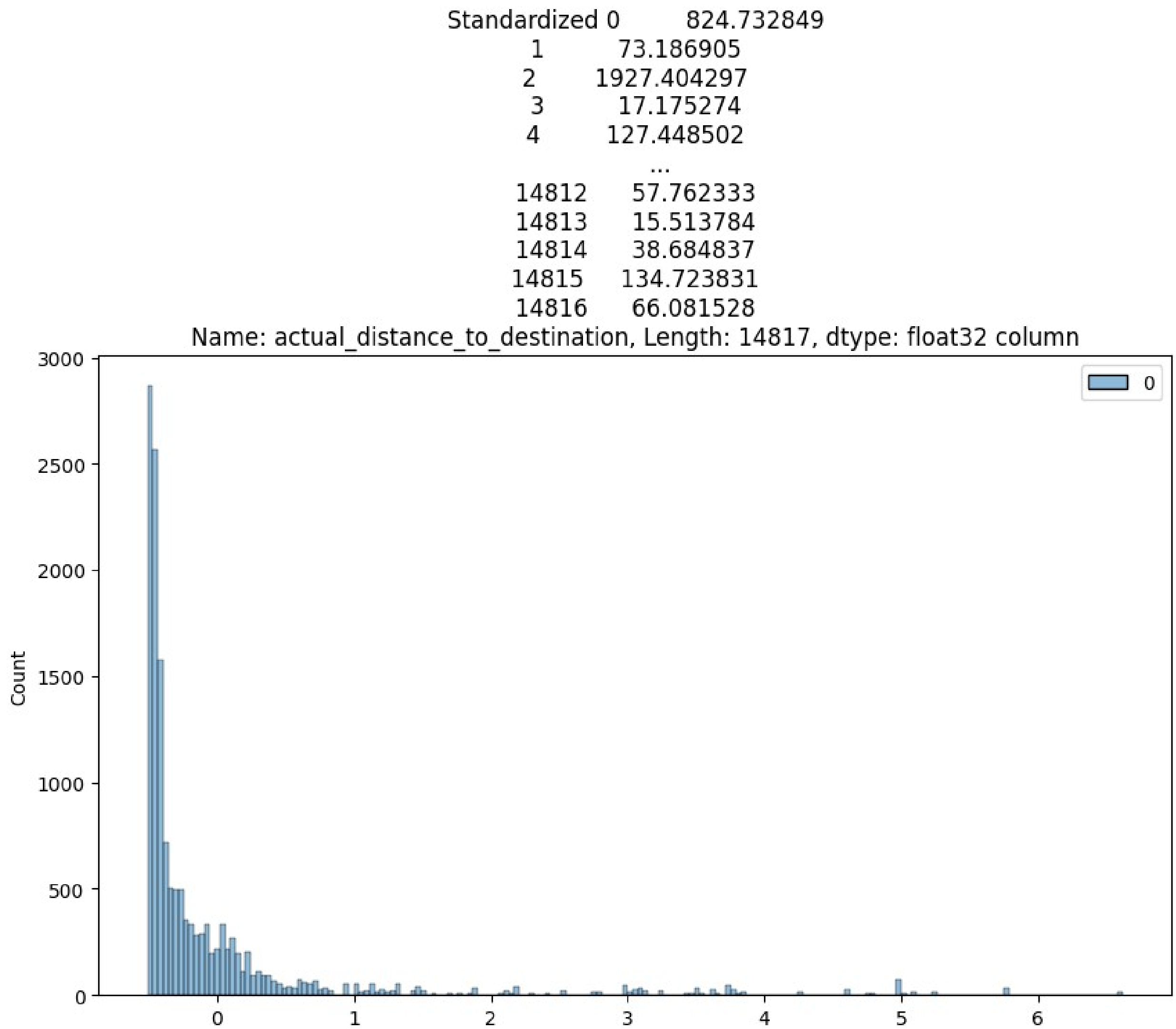
```
from sklearn.preprocessing import StandardScaler

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()

[]
```




```
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()

[]
```

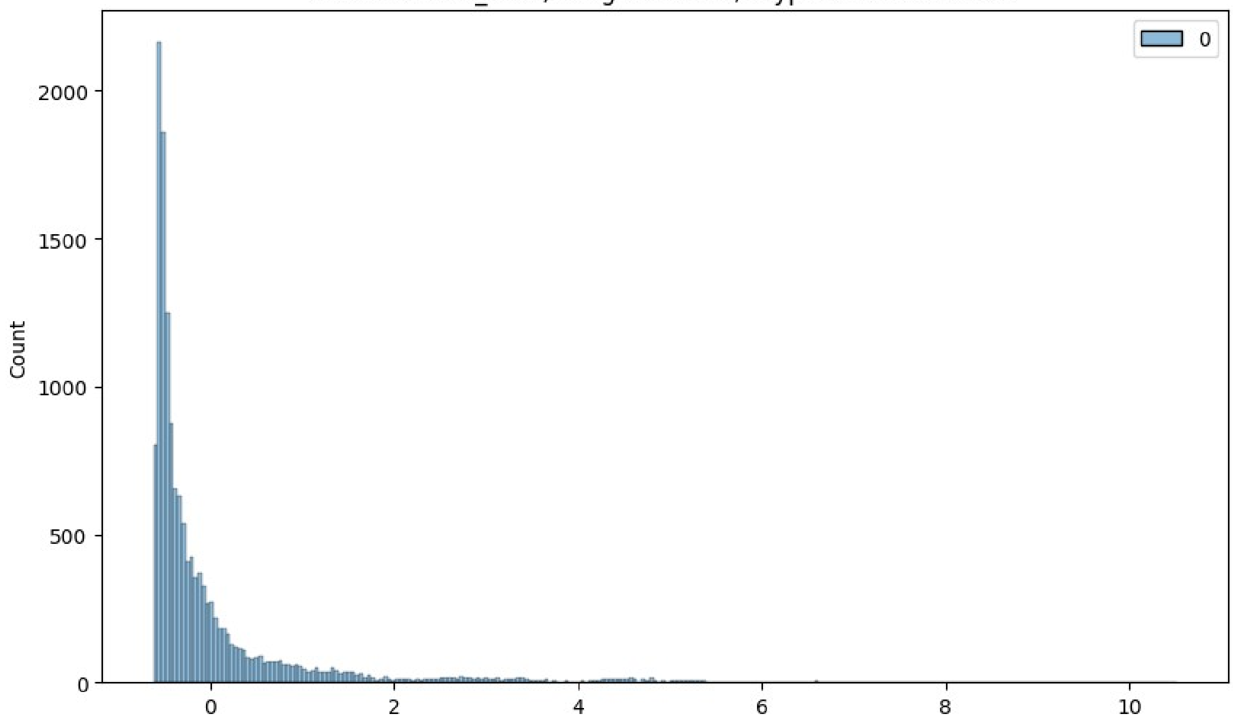



```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled =
scaler.fit_transform(df2['actual_distance_to_destination'].to_numpy().
reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['actual_distance_to_destination']}
column")
plt.plot()

[]
```



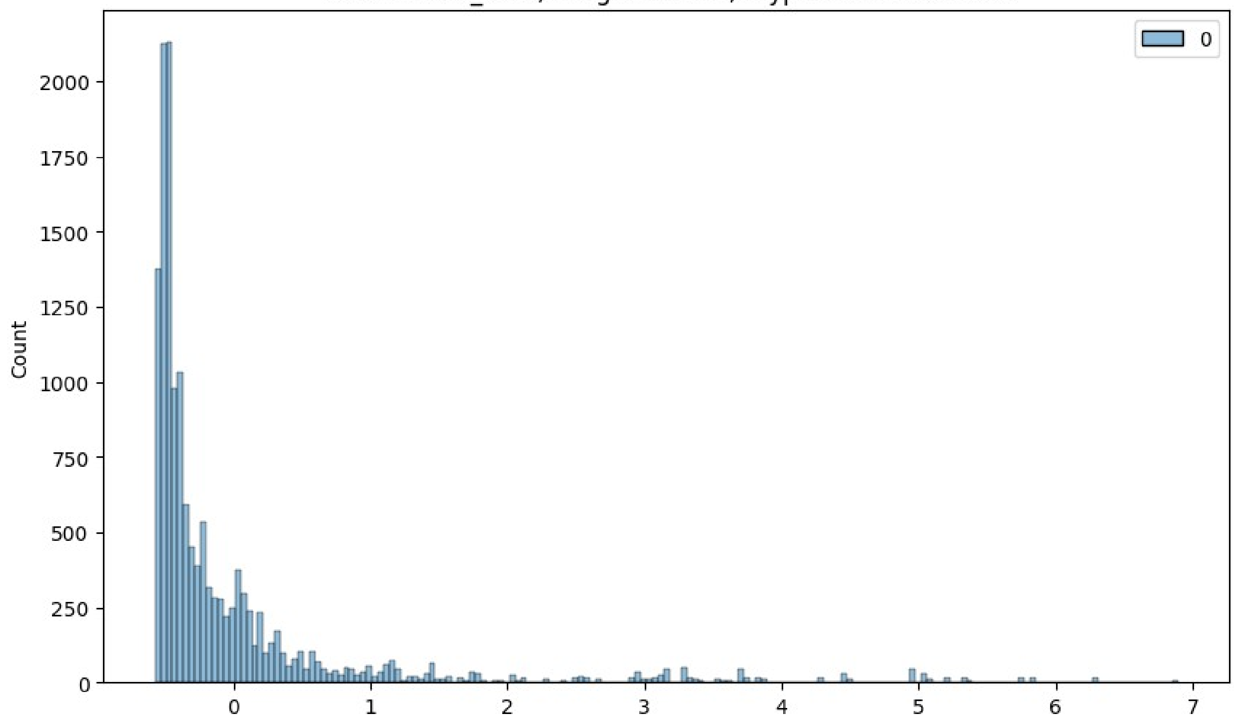

```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['actual_time'].to_numpy().reshape(-
1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['actual_time']} column")
plt.plot()

[]
```

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

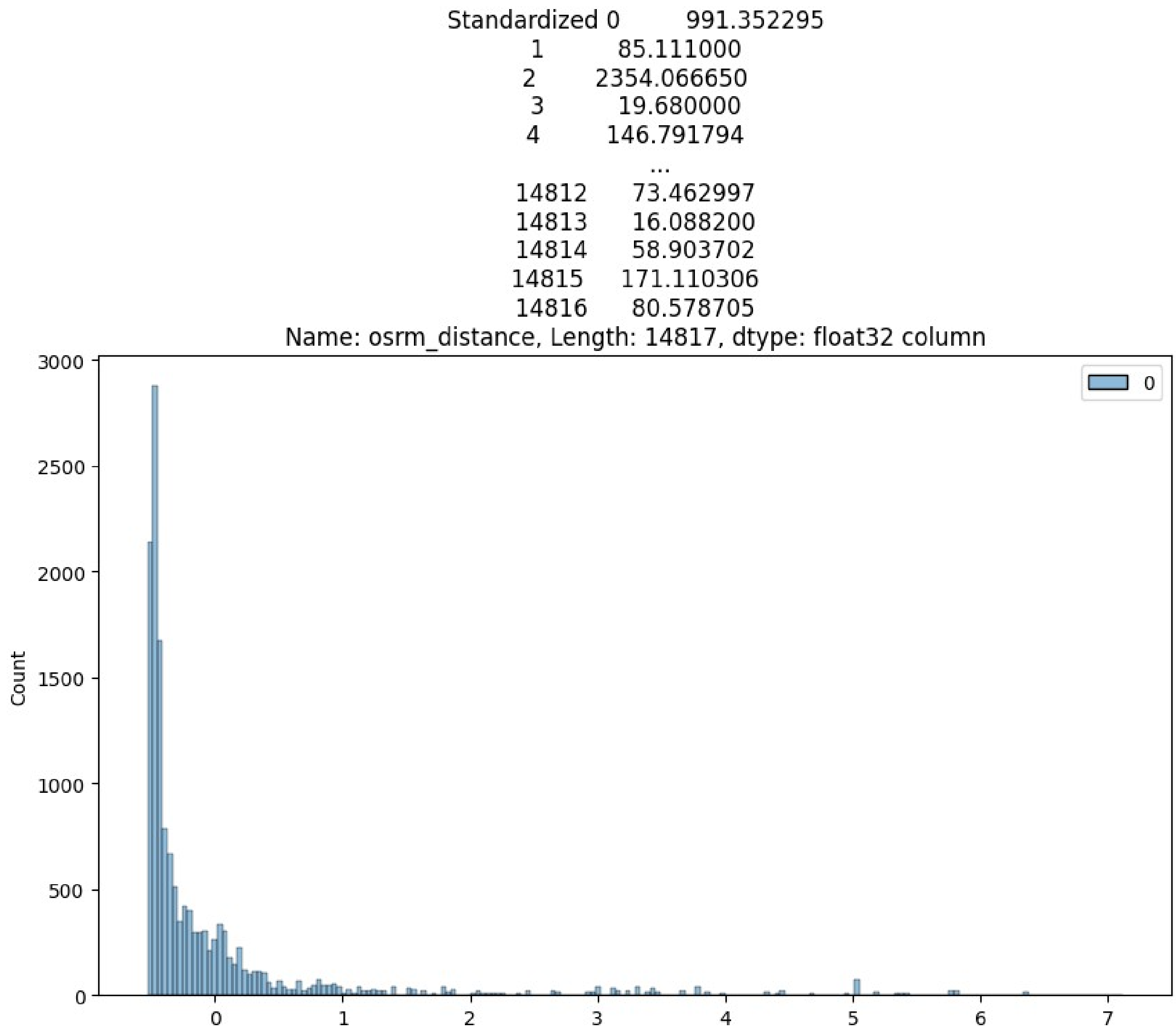



```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['osrm_time'].to_numpy().reshape(-1,
1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['osrm_time']} column")
plt.plot()

[]
```

```
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
```

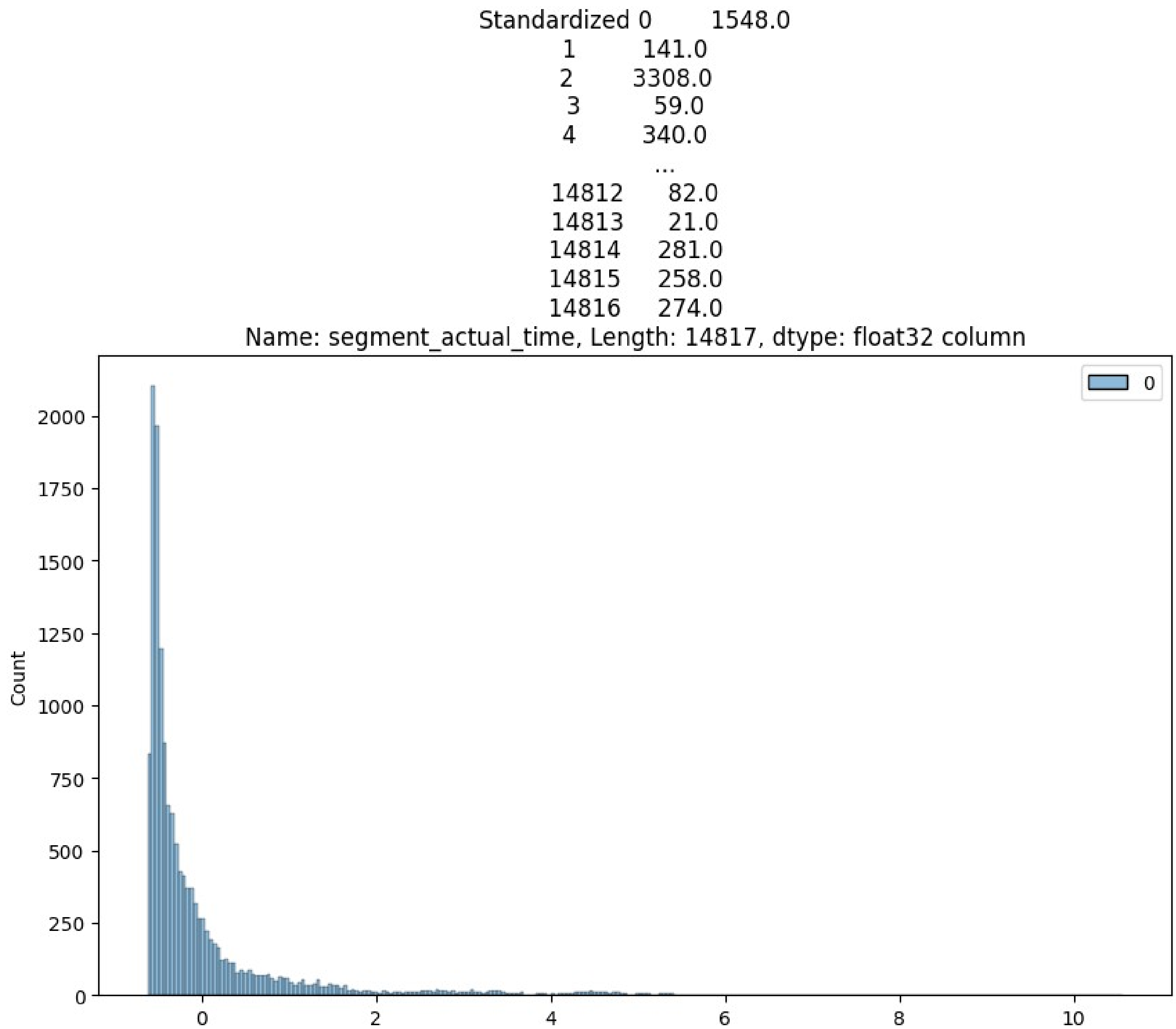



```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled =
scaler.fit_transform(df2['osrm_distance'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['osrm_distance']} column")
plt.plot()

[]
```



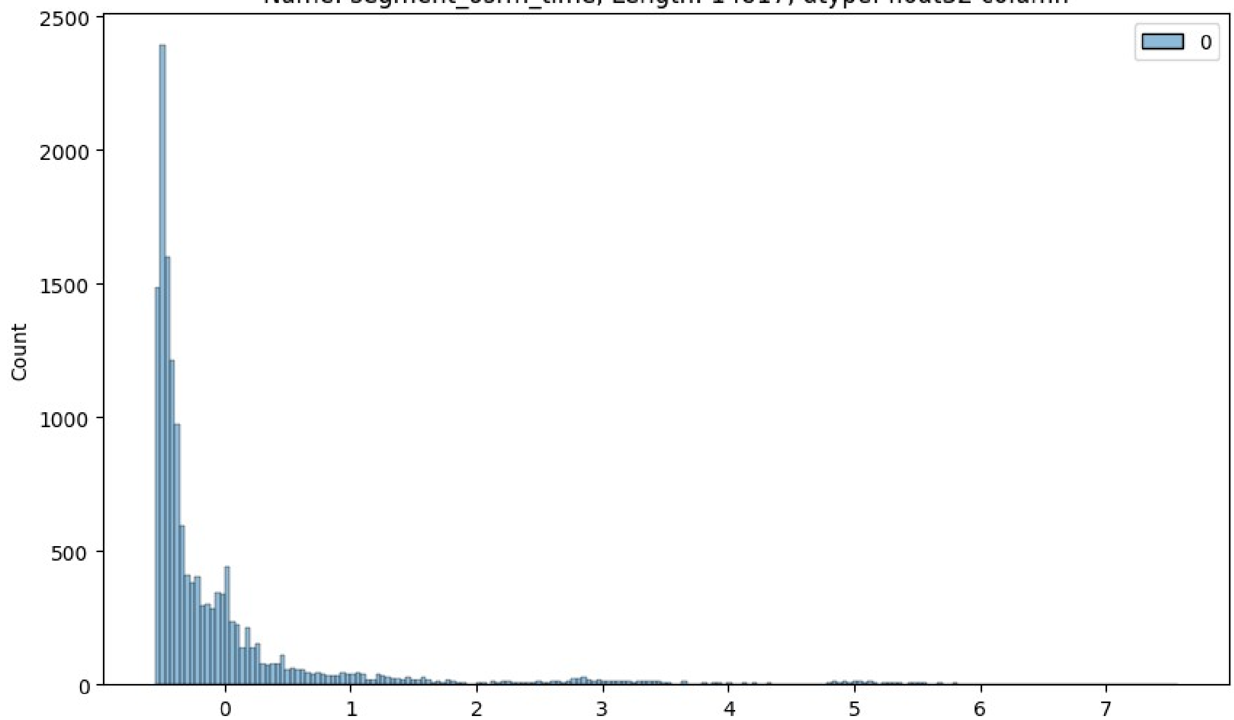

```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled =
scaler.fit_transform(df2['segment_actual_time'].to_numpy().reshape(-1,
1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['segment_actual_time']} column")
plt.plot()
```

```
[]
```



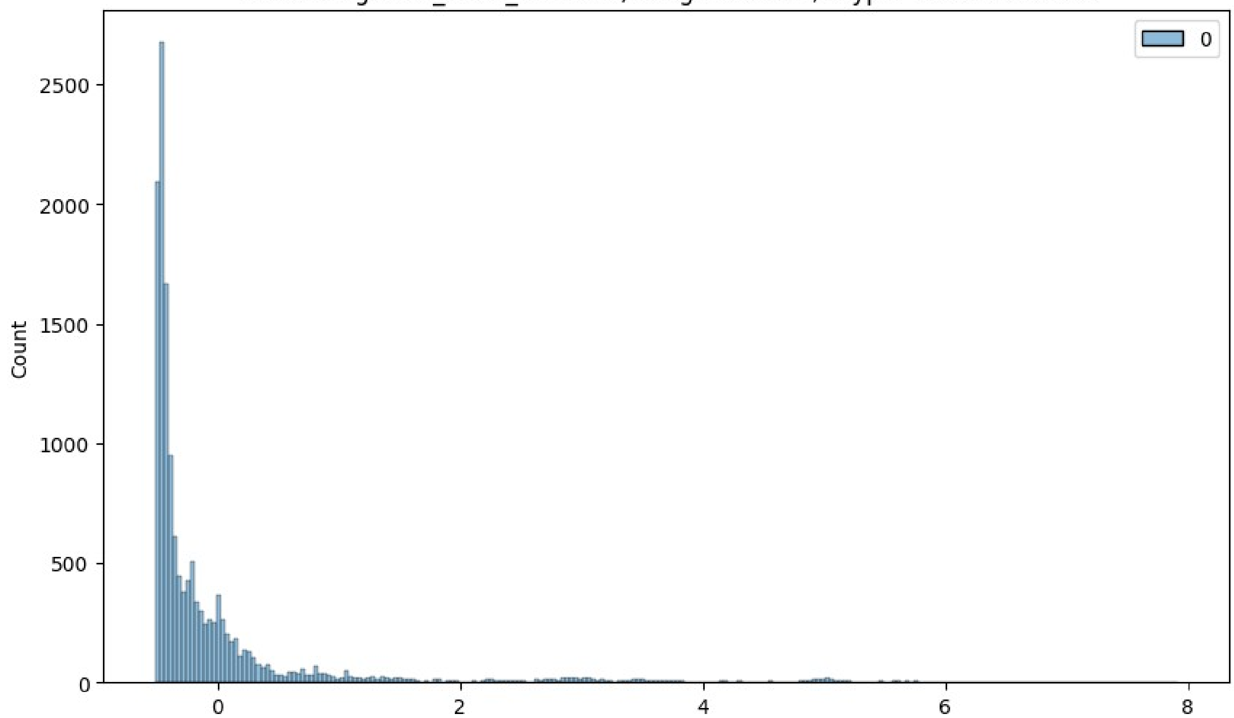

```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled =
scaler.fit_transform(df2['segment_osrm_time'].to_numpy().reshape(-1,
1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['segment_osrm_time']} column")
plt.plot()

[]
```

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




```
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()

[]
```

```
Standardized 0        1320.473267
            1          84.189400
            2        2545.267822
            3          19.876600
            4         146.791901
                         ...
            14812      64.855103
            14813      16.088299
            14814     104.886597
            14815     223.532394
            14816      80.578705
Name: segment_osrm_distance, Length: 14817, dtype: float32 column
```



Business Insights

The dataset spans from '2018-09-12 00:00:16' to '2018-10-08 03:00:24' and includes 14,817 unique trip IDs, 1,508 unique source centers, 1,481 unique destination centers, 690 unique source cities, and 806 unique destination cities.

The majority of the data is allocated for testing purposes, with Carting being the most common route type. Additionally, 14 unique location IDs are missing from the dataset.

Trip volumes exhibit an increasing trend after noon, reaching a peak at 10 P.M., and then gradually decreasing. The 38th week sees the highest number of trips, while mid-month experiences the most significant order influx.

Primary sourcing states include Maharashtra, Karnataka, Haryana, Tamil Nadu, and Telangana. Mumbai leads in trip originations, followed by Gurgaon, Delhi, Bengaluru, and Bhiwandi, indicating strong seller presence.

Maximum trip destinations are in Maharashtra, followed by Karnataka, Haryana, Tamil Nadu, and Uttar Pradesh. Specifically, Mumbai, Bengaluru, Gurgaon, Delhi, and Chennai receive the highest order volumes.

Analysis reveals a statistical similarity between features start_scan_to_end_scan and od_total_time, while features actual_time and osrm_time exhibit statistical differences.

The features start_scan_to_end_scan and segment_actual_time show statistical similarity, whereas osrm_distance and segment_osrm_distance are statistically different.

Both osrm_time and segment_osrm_time are statistically dissimilar, suggesting variations between the two.

In terms of destination, cities such as Bengaluru, Mumbai, Gurgaon, Bangalore, and Delhi dominate order placements.

The provided information underscores the importance of time-related features, showcasing their impact on trip statistics and highlighting regional variations in customer behavior and seller presence.

Recommendations

Here are some key recommendations:

Time-Related Feature Optimization:

Given the observed trend in trip volumes, focus on allocating resources effectively during peak hours around 10 P.M. Consider implementing dynamic pricing or targeted promotions during peak hours to encourage more bookings.

Geographic Strategy:

Recognize the importance of regional variations in customer behavior and seller presence. Tailor marketing and promotional strategies based on the leading cities, such as Mumbai, Bengaluru, Gurgaon, Delhi, and Chennai, to maximize order placements.

Testing and Carting Routes:

Acknowledge that the majority of the data is allocated for testing purposes with Carting being the most common route type. Explore opportunities to leverage Carting routes for potential business growth and consider refining strategies for testing purposes.

Missing Location IDs:

Investigate the 14 unique missing location IDs and assess the impact on the overall dataset. Implement measures to fill in or account for missing location information to ensure comprehensive analysis and accurate decision-making.

Regional Sourcing States:

Capitalize on the strong seller presence in Maharashtra, Karnataka, Haryana, Tamil Nadu, and Telangana. Develop targeted initiatives to attract more sellers from these states and enhance collaboration. **Sourcing State Prioritization:**

Prioritize sourcing efforts in Maharashtra, Karnataka, Haryana, Tamil Nadu, and Telangana, considering their significant contribution to trip volumes.

Statistical Differences:

Address the statistical differences observed between features like actual_time and osrm_time. Investigate the root causes and take corrective actions if necessary to improve accuracy and reliability in these measurements.

Destination-Centric Strategies:

Given the dominance of certain cities in order placements, develop destination-centric strategies for cities like Bengaluru, Mumbai, Gurgaon, Bangalore, and Delhi. This can include targeted promotions, improved logistics, and better customer support.

Mid-Month Order Influx:

Understand the factors contributing to the significant order influx in the mid-month and tailor marketing or promotional activities during that period to maximize customer engagement and orders.

Continuous Monitoring:

Establish a system for continuous monitoring of trip statistics, customer behavior, and seller performance to adapt strategies based on evolving trends and patterns.

```
a+b

----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
<ipython-input-143-ca730b97bf8a> in <cell line: 1>()
----> 1 a+b

NameError: name 'a' is not defined
```