delhivery

August 24, 2024

Business Problem

- Clean, sanitize and manipulate data to get useful features out of raw fields. Make sense out of the raw data and help the data science team to build forecasting models on it.

Delhivery

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

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

Column Profiling:

- data - tells whether the data is testing or training data
- trip_creation_time -Timestamp of trip creation
- route_schedule_uuid - Unique Id for a particular route schedule
- route_type - Transportation type:
  - FTL - Full Truck Load: FTL shipments get to the destination sooner, as the truck is making no other pickups or drop-offs along the way
  - Carting: Handling system consisting of small vehicles (carts)

- trip_uuid - Unique ID given to a particular trip (A trip may include different source and destination centers)
- source_center - Source ID of trip origin
- source_name - Source Name of trip origin
- destination_cente - Destination ID
- destination_name - Destination Name
- od_start_time - Trip start time
- od_end_time - Trip end time
- start_scan_to_end_scan - Time taken to deliver from source to destination
- is_cutoff - Unknown field
- cutoff_factor 0- Unknown field
- cutoff_timestamp - Unknown field
- actual_distance_to_destination - Distance in Kms between source and destination warehouse

- actual_time - Actual time taken to complete the delivery (Cumulative)
- osrm_time - An open-source routing engine time calculator which computes the shortest path between points in a given map (Includes usual traffic, distance through major and minor roads) and gives the time (Cumulative)
- osrm_distance - An open-source routing engine which computes the shortest path between points in a given map (Includes usual traffic, distance through major and minor roads) (Cumulative)
- factor - Unknown field
- segment_actual_time - This is a segment time. Time taken by the subset of the package delivery
- segment_osrm_time - This is the OSRM segment time. Time taken by the subset of the package delivery
- segment_osrm_distance - This is the OSRM distance. Distance covered by subset of the package delivery
- segment_factor - Unknown field

Objectives of the Project

- Perform EDA on the given dataset and find insights.
- Provide Useful Insights and Business recommendations that can help the business to grow.

Import libraries

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import warnings
warnings.filterwarnings('ignore')
import gdown as gd
from sklearn.impute import SimpleImputer
```

Loading the data

[ ]:
```
!gdown 1-NaCUyRnUHzvhCLaBbELxrrzEWdWx6M6
```

```
Downloading…
From: https://drive.google.com/uc?id=1-NaCUyRnUHzvhCLaBbELxrrzEWdWx6M6
To: /content/delhivery_data.csv
100% 55.6M/55.6M [00:00<00:00, 80.9MB/s]
```

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

Basic Observation

[ ]:
```
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]
```

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

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

[ ]:
```
df.ndim
```

[ ]:
```
2
```

Delhivery dataset, there are 144867 rows and 24 columns and 2 dimensions.

[ ]:
```
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')
```

[ ]:
```
df.dtypes
```

[ ]:
```
data                                  object
trip_creation_time                    object
route_schedule_uuid                   object
route_type                            object
trip_uuid                             object
source_center                         object
source_name                           object
destination_center                    object
destination_name                      object
od_start_time                         object
od_end_time                           object
start_scan_to_end_scan               float64
is_cutoff                               bool
cutoff_factor                          int64
cutoff_timestamp                      object
```

```
actual_distance_to_destination    float64
actual_time                       float64
osrm_time                         float64
osrm_distance                     float64
factor                            float64
segment_actual_time               float64
segment_osrm_time                 float64
segment_osrm_distance             float64
segment_factor                    float64
dtype: object
```

[ ]:
```
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
```

The data types include float64,int64(for integer data,object (for text/string data) and datetimes64.

[ ]:
```
unknown_fields = ['is_cutoff', 'cutoff_factor', 'cutoff_timestamp', 'factor',␣
↪'segment_factor']
# Check which fields actually exist in your DataFrame
existing_fields = [field for field in unknown_fields if field in df.columns]
df = df.drop(columns=existing_fields)
```

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

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

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

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

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

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

```
2191.4037000000003
```

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

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

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

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

Missing value detection & cleaning

```
[ ]: def missing_to_df(df):
         total_missing_df = df.isnull().sum().sort_values(ascending =False)
         percent_missing_df = (df.isnull().sum()/len(df)*100).
      ↪sort_values(ascending=False)
         missing_data_df = pd.concat([total_missing_df, percent_missing_df], axis=1,␣
      ↪keys=['Total', 'Percent'])
         return missing_data_df
```

```
[ ]: missing_to_df(df)
```

[ ]:

	Total	Percent
source_name	293	0.202254
destination_name	261	0.180165
data	0	0.000000
start_scan_to_end_scan	0	0.000000
segment_osrm_time	0	0.000000
segment_actual_time	0	0.000000
osrm_distance	0	0.000000
osrm_time	0	0.000000
actual_time	0	0.000000
actual_distance_to_destination	0	0.000000
od_start_time	0	0.000000
od_end_time	0	0.000000
trip_creation_time	0	0.000000
destination_center	0	0.000000
source_center	0	0.000000
trip_uuid	0	0.000000
route_type	0	0.000000
route_schedule_uuid	0	0.000000
segment_osrm_distance	0	0.000000

There are two columns: one is source_name, which has 293 missing values, and the other is destination_name, which has 261 missing values.

[ ]:
```
cat_missing = ['source_name', 'destination_name']
freq_imputer = SimpleImputer(strategy = 'most_frequent')
for col in cat_missing:
    df[col] = pd.DataFrame(freq_imputer.fit_transform(pd.DataFrame(df[col])))
```

[ ]:
```
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
```

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

[ ]:
```
                                   count                            mean  \
trip_creation_time                144867   2018-09-22 13:34:23.659819264
od_start_time                     144867   2018-09-22 18:02:45.855230720
od_end_time                       144867   2018-09-23 10:04:31.395393024
start_scan_to_end_scan          144867.0                      961.262986
actual_distance_to_destination  144867.0                       234.07338
actual_time                     144867.0                      416.927521
osrm_time                       144867.0                      213.868286
osrm_distance                   144867.0                      284.771301
segment_actual_time             144867.0                        36.19611
segment_osrm_time               144867.0                       18.507547
segment_osrm_distance           144867.0                       22.829018

                                                       min  \
trip_creation_time              2018-09-12 00:00:16.535741
od_start_time                   2018-09-12 00:00:16.535741
od_end_time                     2018-09-12 00:50:10.814399
```

```
start_scan_to_end_scan                             20.0
actual_distance_to_destination                 9.000046
actual_time                                         9.0
osrm_time                                           6.0
osrm_distance                                    9.0082
segment_actual_time                              -244.0
segment_osrm_time                                   0.0
segment_osrm_distance                               0.0

                                                  25%  \
trip_creation_time              2018-09-17 03:20:51.775845888
od_start_time                   2018-09-17 08:05:40.886155008
od_end_time                     2018-09-18 01:48:06.410121984
start_scan_to_end_scan                              161.0
actual_distance_to_destination                  23.355875
actual_time                                          51.0
osrm_time                                            27.0
osrm_distance                                   29.914701
segment_actual_time                                  20.0
segment_osrm_time                                    11.0
segment_osrm_distance                             12.0701

                                                  50%  \
trip_creation_time              2018-09-22 04:24:27.932764928
od_start_time                   2018-09-22 08:53:00.116656128
od_end_time                     2018-09-23 03:13:03.520212992
start_scan_to_end_scan                              449.0
actual_distance_to_destination                  66.126572
actual_time                                         132.0
osrm_time                                            64.0
osrm_distance                                   78.525803
segment_actual_time                                  29.0
segment_osrm_time                                    17.0
segment_osrm_distance                              23.513

                                                  75%  \
trip_creation_time              2018-09-27 17:57:56.350054912
od_start_time                   2018-09-27 22:41:50.285857024
od_end_time                     2018-09-28 12:49:06.054018048
start_scan_to_end_scan                             1634.0
actual_distance_to_destination                 286.708878
actual_time                                         513.0
osrm_time                                           257.0
osrm_distance                                  343.193253
segment_actual_time                                  40.0
segment_osrm_time                                    22.0
segment_osrm_distance                            27.81325
```

```
                                                    max            std
trip_creation_time              2018-10-03 23:59:42.701692            NaN
od_start_time                   2018-10-06 04:27:23.392375            NaN
od_end_time                     2018-10-08 03:00:24.353479            NaN
start_scan_to_end_scan                              7898.0    1037.012769
actual_distance_to_destination                 1927.447754     344.990021
actual_time                                         4532.0     598.103638
osrm_time                                           1686.0     308.011078
osrm_distance                                  2326.199219     421.119293
segment_actual_time                                 3051.0      53.571156
segment_osrm_time                                   1611.0       14.77596
segment_osrm_distance                          2191.403809      17.860661
```

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

[ ]:
```
                       count  unique  \
route_schedule_uuid   144867    1504
trip_uuid             144867   14817
source_center         144867    1508
source_name           144867    1498
destination_center    144867    1481
destination_name      144867    1468

                                                                   top   freq
route_schedule_uuid  thanos::sroute:4029a8a2-6c74-4b7e-a6d8-f9e069f…   1812
trip_uuid                                    trip-153811219535896559    101
source_center                                            IND000000ACB  23347
source_name                                Gurgaon_Bilaspur_HB (Haryana)  23640
destination_center                                       IND000000ACB  15192
destination_name                           Gurgaon_Bilaspur_HB (Haryana)  15453
```

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]
```

Calculate the 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]
```

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

```
[ ]: 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'],
      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 : 689
```

[ ]:
```
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(10)
```

[ ]:
```
0        Kanpur
1    Doddablpur
2       Gurgaon
3        Mumbai
4        Sandur
5       Chennai
6       Chennai
7     Bengaluru
8         Surat
9         Delhi
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
```

Comparison & Visualization of time and distance fields

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
```

[ ]:
```
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)
```

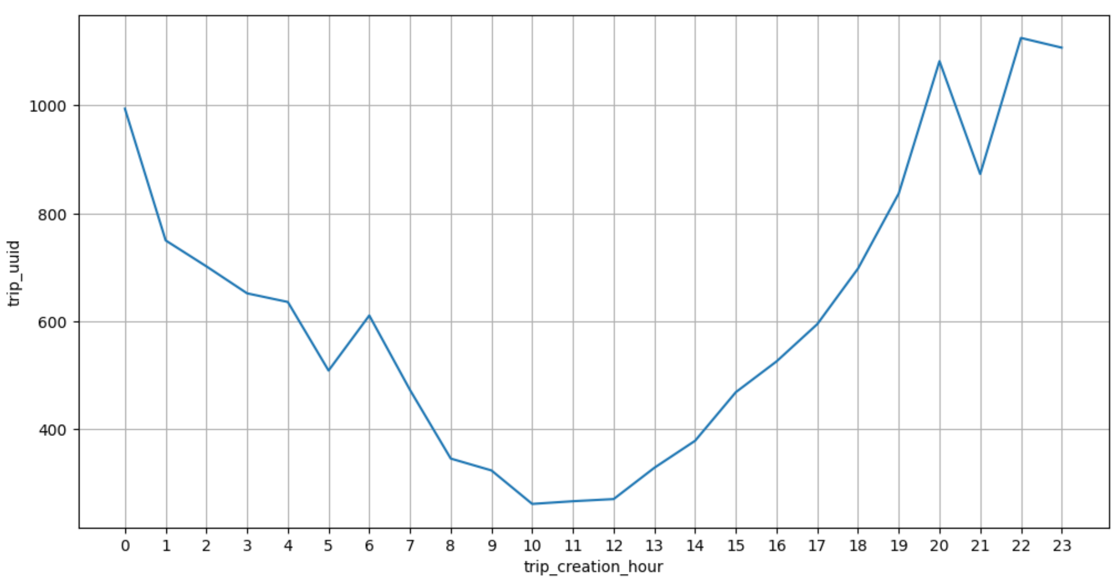
[ ]:
```
df_hour = df2.groupby(by = 'trip_creation_hour')['trip_uuid'].count().
 ↪to_frame().reset_index()
df_hour.head()
```

[ ]:

	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()
```

[ ]:
```
[]
```



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

[ ]:
```
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)
```

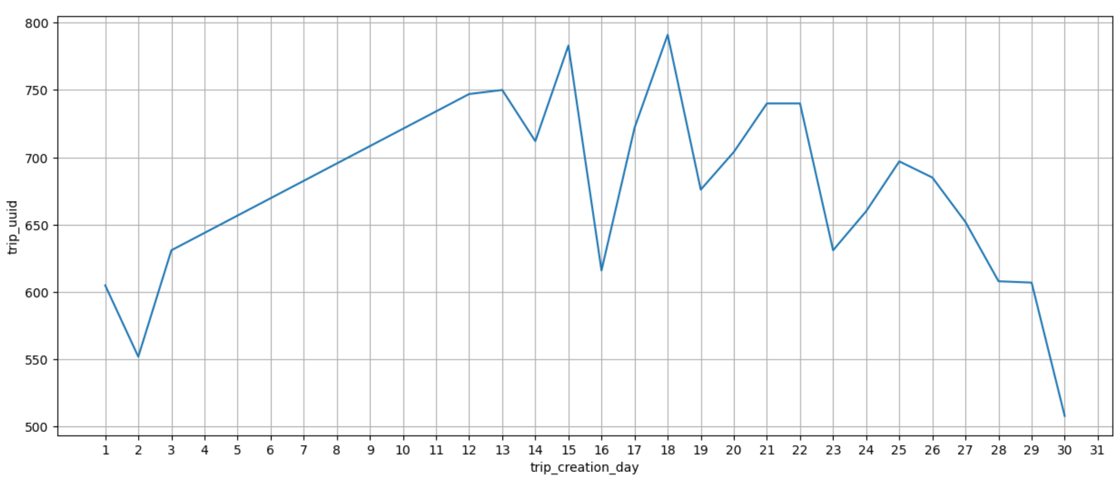
[ ]:
```
df_day = df2.groupby(by = 'trip_creation_day')['trip_uuid'].count().to_frame().
 ↪reset_index()
df_day.head()
```

[ ]:

	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()
```

[ ]: []



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

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

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

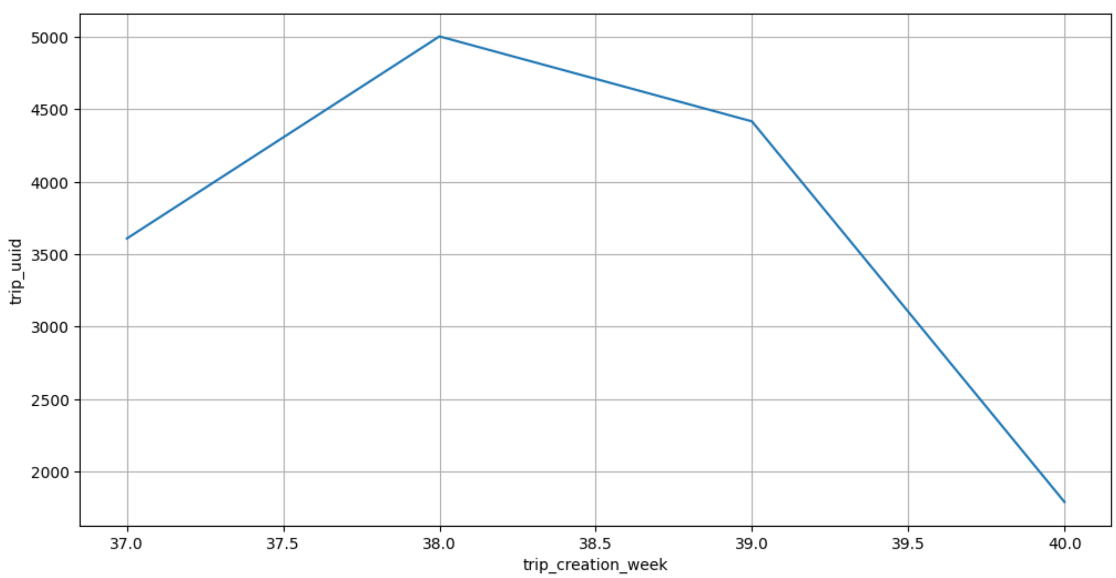
[ ]:
```
df_week = df2.groupby(by = 'trip_creation_week')['trip_uuid'].count().
↪to_frame().reset_index()
df_week.head()
```

[ ]:

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

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

[ ]:
```
[]
```



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

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

[ ]:
```
                                 count                           mean  \
trip_creation_time               14817  2018-09-22 12:44:19.555167744
od_total_time                  14817.0                      531.69763
start_scan_to_end_scan         14817.0                     530.810016
actual_distance_to_destination 14817.0                     164.477829
actual_time                    14817.0                     357.143768
osrm_time                      14817.0                     161.384018
osrm_distance                  14817.0                     204.344711
segment_actual_time            14817.0                     353.892273
segment_osrm_time              14817.0                     180.949783
segment_osrm_distance          14817.0                     223.201157
trip_creation_date               14817  2018-09-21 23:46:58.627252736
trip_creation_day              14817.0                       18.37079
trip_creation_month            14817.0                       9.120672
trip_creation_year             14817.0                         2018.0
trip_creation_week             14817.0                      38.295944
trip_creation_hour             14817.0                      12.449821

                                                       min  \
trip_creation_time             2018-09-12 00:00:16.535741
od_total_time                                        23.46
start_scan_to_end_scan                                23.0
actual_distance_to_destination                    9.002461
actual_time                                            9.0
osrm_time                                              6.0
osrm_distance                                       9.0729
segment_actual_time                                    9.0
segment_osrm_time                                      6.0
segment_osrm_distance                               9.0729
trip_creation_date                     2018-09-12 00:00:00
trip_creation_day                                      1.0
trip_creation_month                                    9.0
trip_creation_year                                  2018.0
trip_creation_week                                    37.0
trip_creation_hour                                     0.0

                                                          25%  \
trip_creation_time             2018-09-17 02:51:25.129125888
od_total_time                                          149.93
start_scan_to_end_scan                                  149.0
actual_distance_to_destination                      22.837238
actual_time                                              67.0
osrm_time                                                29.0
osrm_distance                                       30.819201
segment_actual_time                                      66.0
```

```
segment_osrm_time                                          31.0
segment_osrm_distance                                 32.654499
trip_creation_date                          2018-09-17 00:00:00
trip_creation_day                                          14.0
trip_creation_month                                         9.0
trip_creation_year                                       2018.0
trip_creation_week                                         38.0
trip_creation_hour                                          4.0

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

                                                            75%  \
trip_creation_time              2018-09-27 19:37:41.898427904
od_total_time                                             638.2
start_scan_to_end_scan                                    637.0
actual_distance_to_destination                       164.583206
actual_time                                               370.0
osrm_time                                                 168.0
osrm_distance                                        208.475006
segment_actual_time                                       367.0
segment_osrm_time                                         185.0
segment_osrm_distance                                218.802399
trip_creation_date                          2018-09-27 00:00:00
trip_creation_day                                          25.0
trip_creation_month                                         9.0
trip_creation_year                                       2018.0
trip_creation_week                                         39.0
trip_creation_hour                                         20.0

                                                         max         std
trip_creation_time              2018-10-03 23:59:42.701692         NaN
```

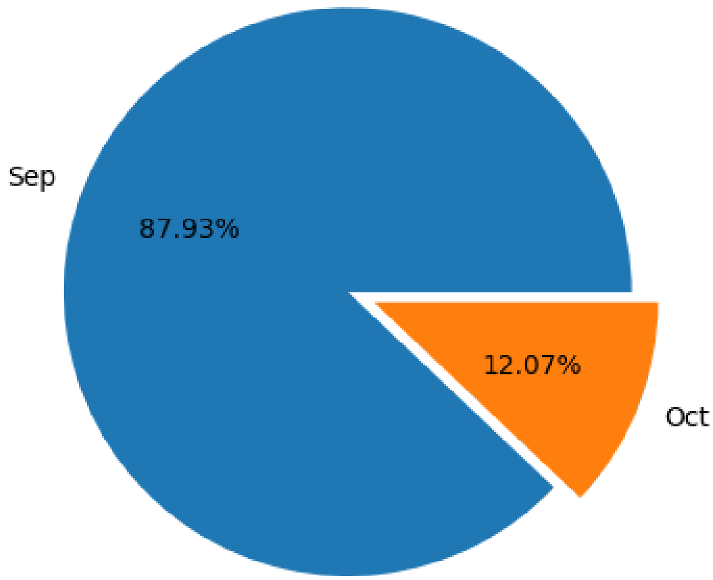
```
od_total_time                                   7898.55  658.868223
start_scan_to_end_scan                           7898.0  658.705957
actual_distance_to_destination              2186.531738  305.388153
actual_time                                      6265.0  561.396118
osrm_time                                        2032.0  271.360992
osrm_distance                               2840.081055  370.395569
segment_actual_time                              6230.0  556.247925
segment_osrm_time                                2564.0  314.542053
segment_osrm_distance                       3523.632324  416.628387
trip_creation_date                  2018-10-03 00:00:00         NaN
trip_creation_day                                  30.0    7.893275
trip_creation_month                                10.0    0.325757
trip_creation_year                               2018.0         0.0
trip_creation_week                                 40.0    0.967872
trip_creation_hour                                 23.0    7.986553
```

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

[ ]:
```
   trip_creation_month  trip_uuid   perc
0                    9      13029  87.93
1                   10       1788  12.07
```

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

[ ]:
```
[]
```



The data shows information for trips created in two months:

September: Most of the trips were created in September. October : A smaller portion of trips were created in October.

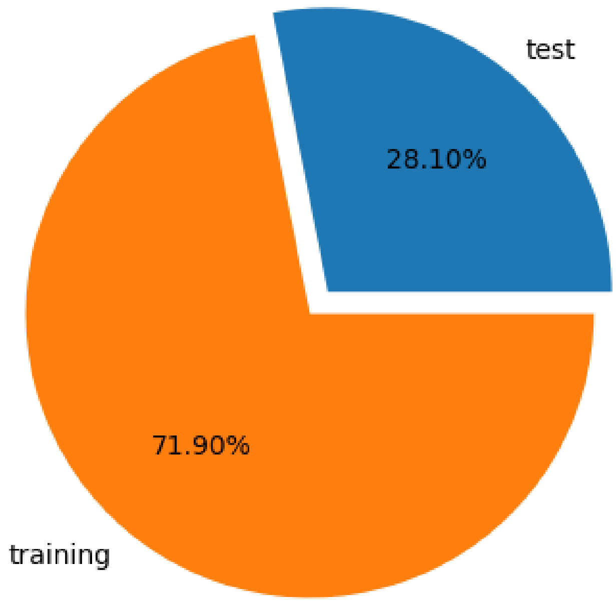
[ ]:
```
df_data = df2.groupby(by = 'data')['trip_uuid'].count().to_frame().reset_index()
df_data['perc'] = np.round(df_data['trip_uuid'] * 100/ df_data['trip_uuid'].
    ↪sum(), 2)
df_data.head()
```

[ ]:

	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()
```

[ ]: []



The perc column indicates the percentage of trips for each set:

- Test Set : The test set comprises 28.1% of the total trips.
- Training Set: The training set comprises 71.9% of the total trips.

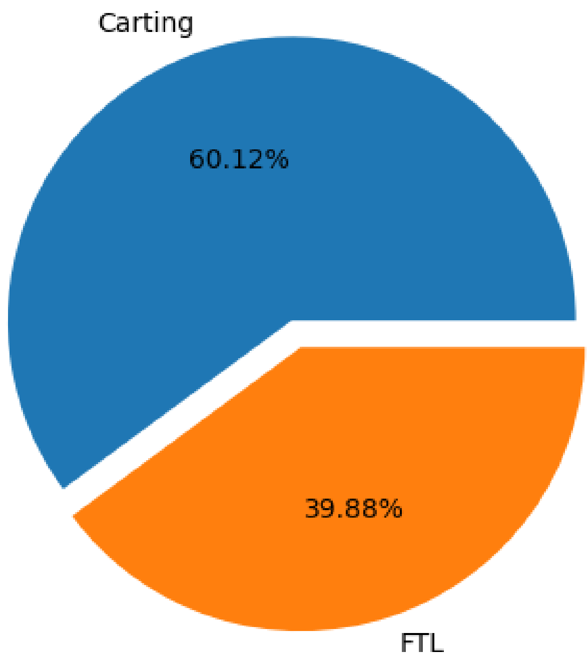
[ ]:
```
df_route = df2.groupby(by = 'route_type')['trip_uuid'].count().to_frame().
    ↪reset_index()
df_route['perc'] = np.round(df_route['trip_uuid'] * 100/ df_route['trip_uuid'].
    ↪sum(), 2)
df_route.head()
```

[ ]:

	route_type	trip_uuid	perc
0	Carting	8908	60.12
1	FTL	5909	39.88

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

[ ]: []



The perc column indicates the percentage of trips for each route type:

- Carting (60.12%): The Carting route type comprises 60.12% of the total trips.
- FTL (39.88%): The FTL route type comprises 39.88% of the total trips.

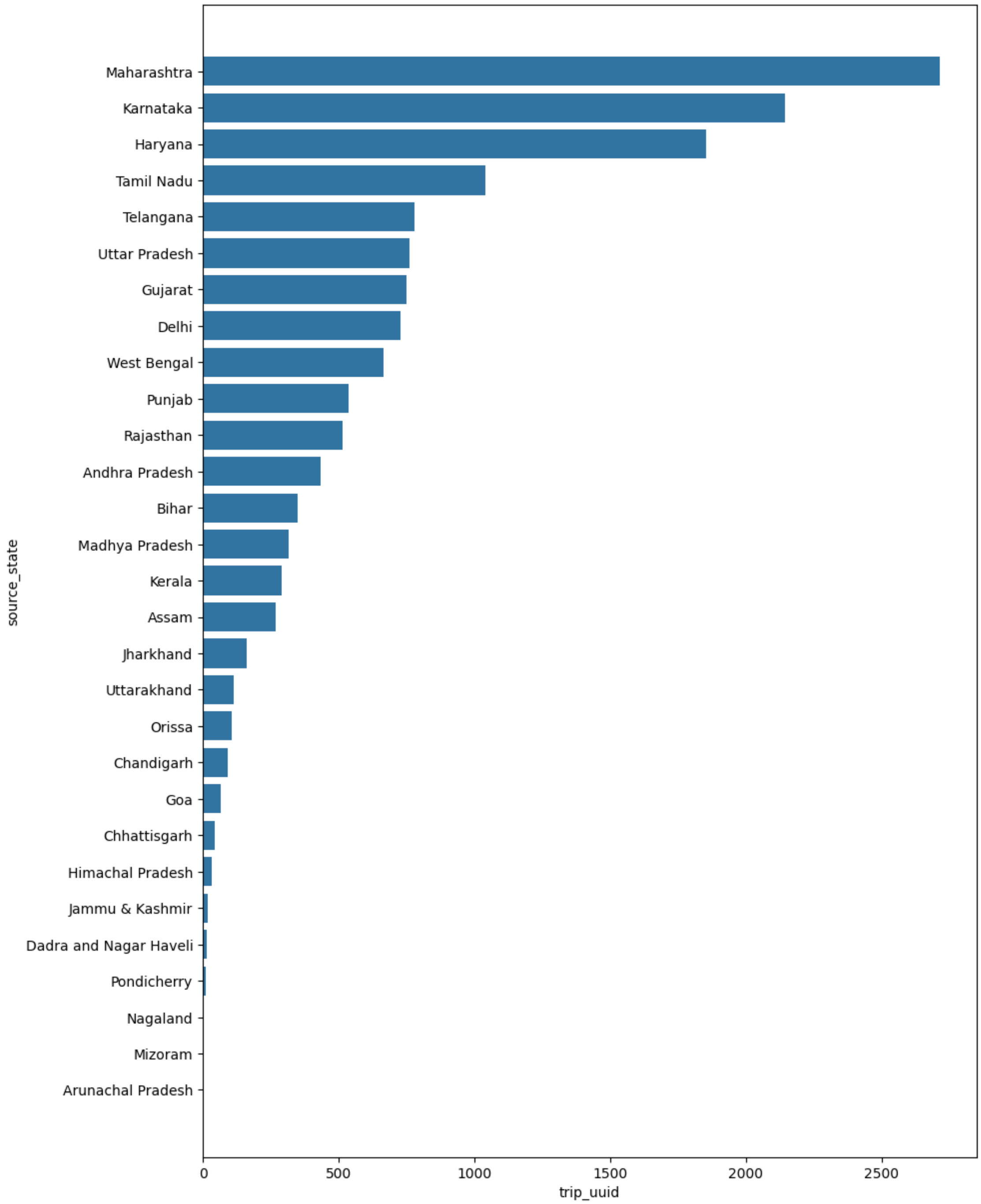
[ ]:
```
df_source_state = df2.groupby(by = 'source_state')['trip_uuid'].count().
 ↪to_frame().reset_index()
df_source_state['perc'] = np.round(df_source_state['trip_uuid'] * 100/␣
 ↪df_source_state['trip_uuid'].sum(), 2)
df_source_state = df_source_state.sort_values(by = 'trip_uuid', ascending =␣
 ↪False)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

[ ]:

	source_state	trip_uuid	perc
17	Maharashtra	2714	18.32
14	Karnataka	2143	14.46
10	Haryana	1854	12.51
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()
```

[ ]: []



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

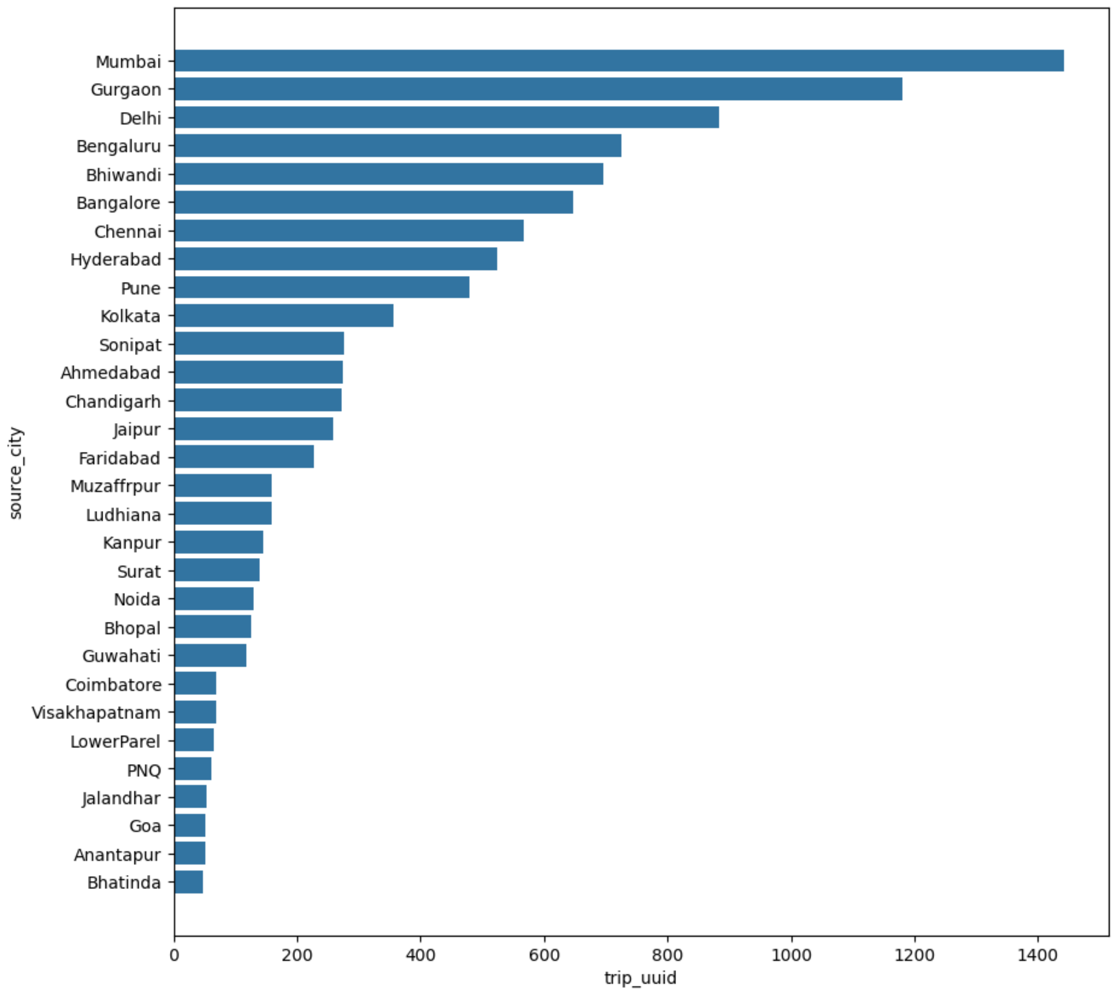
[ ]:
```
df_source_city = df2.groupby(by = 'source_city')['trip_uuid'].count().
    ↪to_frame().reset_index()
df_source_city['perc'] = np.round(df_source_city['trip_uuid'] * 100/
    ↪df_source_city['trip_uuid'].sum(), 2)
df_source_city = df_source_city.sort_values(by = 'trip_uuid', ascending =
    ↪False)[:30]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

[ ]:

	source_city	trip_uuid	perc
439	Mumbai	1442	9.73
237	Gurgaon	1181	7.97
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
93	Bhatinda	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.

[ ]:
```
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()
```

[ ]:

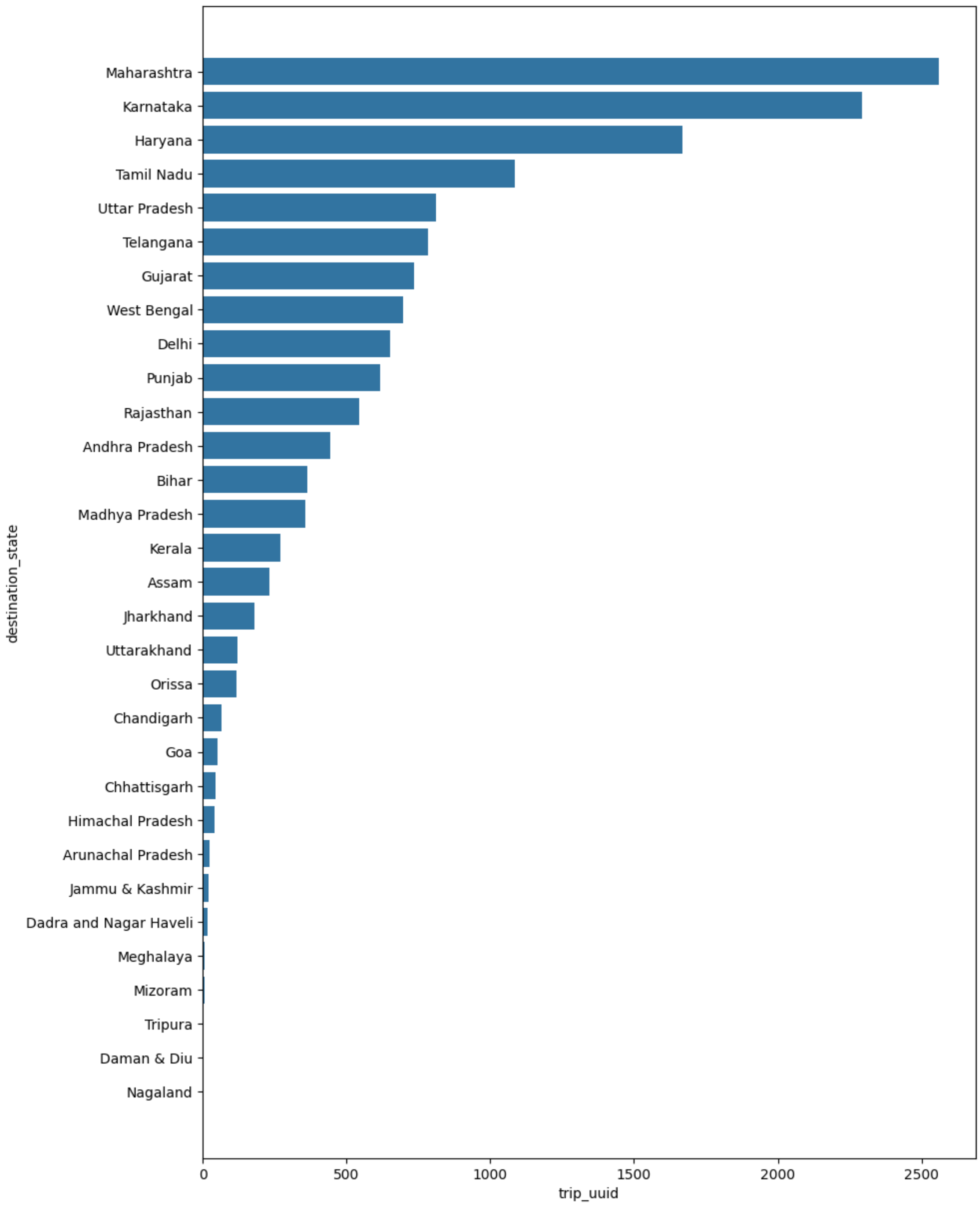
	destination_state	trip_uuid	perc
18	Maharashtra	2561	17.28
15	Karnataka	2294	15.48
11	Haryana	1670	11.27
25	Tamil Nadu	1084	7.32

```
28      Uttar Pradesh         811   5.47
```

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.

```
[ ]: 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.

[ ]:
```
df_destination_city = df2.groupby(by='destination_city')['trip_uuid'].count().
    ↪to_frame().reset_index()
```

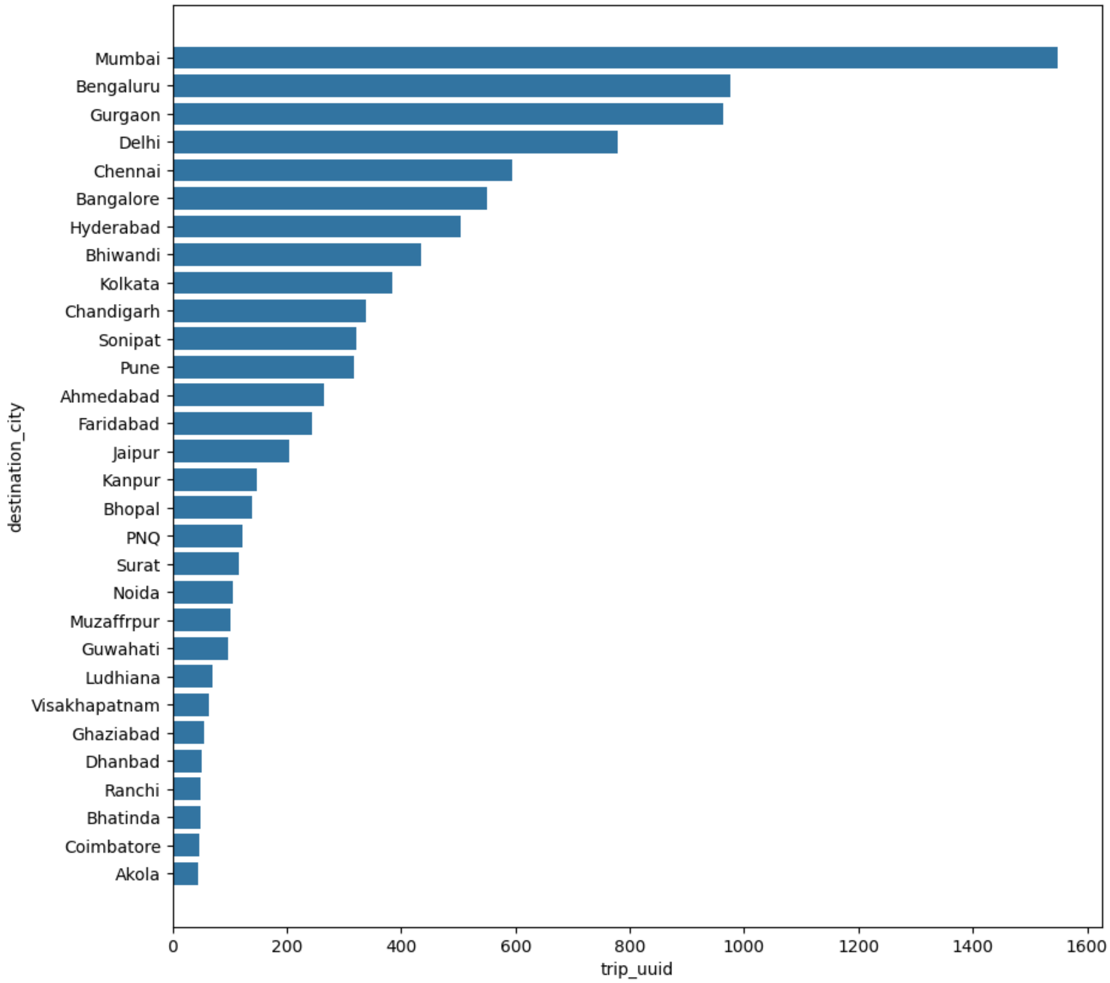
```
df_destination_city['perc'] = np.round(df_destination_city['trip_uuid'] * 100 /␣
↪df_destination_city['trip_uuid'].sum(), 2)
df_destination_city = df_destination_city.sort_values(by='trip_uuid',␣
↪ascending=False)[:30]
df_destination_city
```

[ ]:

	destination_city	trip_uuid	perc
515	Mumbai	1548	10.45
96	Bengaluru	975	6.58
282	Gurgaon	963	6.50
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()
```

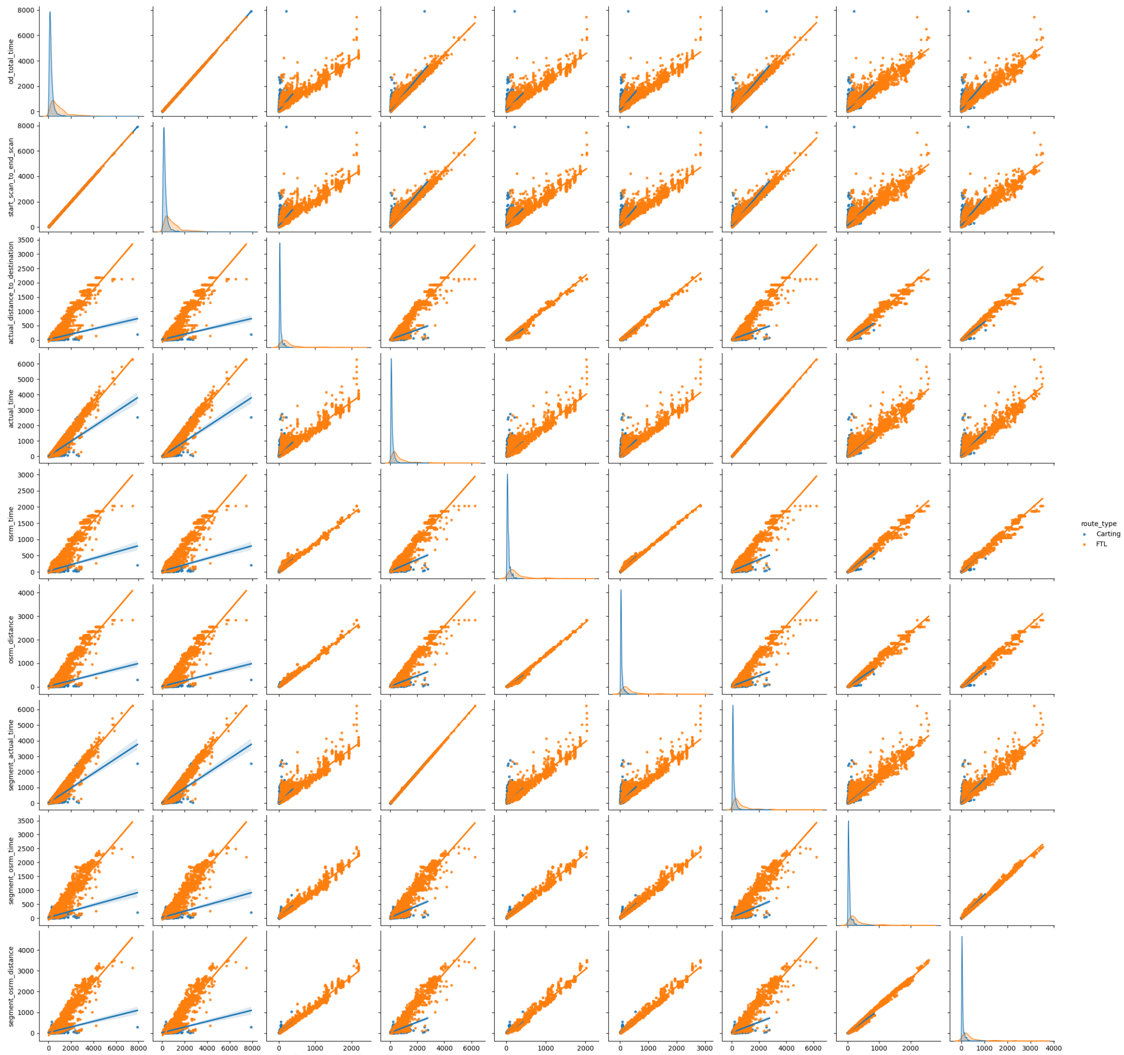
[ ]: []



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']
sns.pairplot(data = df2,
             vars = numerical_columns,
             kind = 'reg',
             hue = 'route_type',
             markers = '.')
plt.plot()
```

[ ]: []



[ ]:
```
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

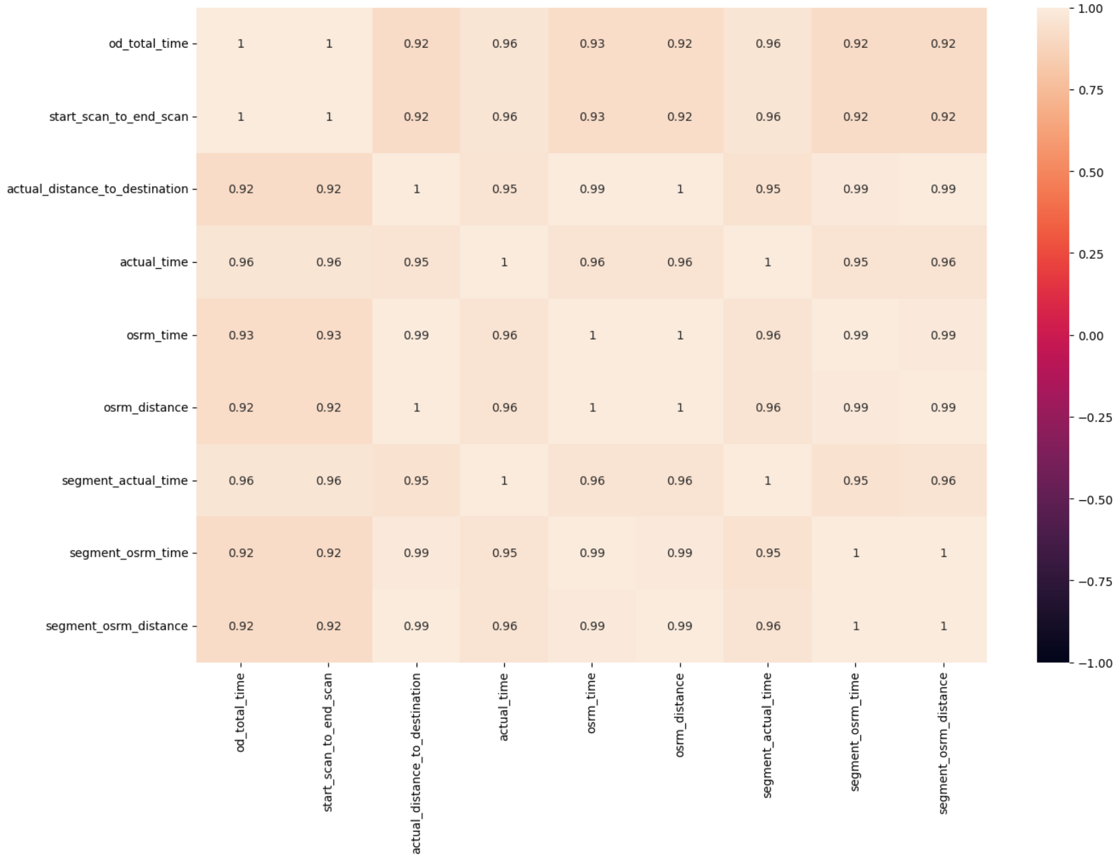
```
segment_osrm_distance                  0.919199               0.919291

                               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.show()
```



In-depth analysis and feature engineering:

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

- STEP-1 : Set up Null Hypothesis
  - Null Hypothesis (H0) - od_total_time (Total Trip Time) and start_scan_to_end_scan (Expected total trip time) are same.
  - Alternate Hypothesis (HA) - od_total_time (Total Trip Time) and start_scan_to_end_scan (Expected total trip time) are different.
- STEP-2 : Checking for basic assumpitons for the hypothesis
  - Distribution check using QQ Plot
  - Homogeneity of Variances using Lavene's test
- STEP-3: Define Test statistics; Distribution of T under H0. If the assumptions of T Test are met then we can proceed performing T Test for independent samples else we will perform the non parametric test equivalent to T Test for independent sample i.e., Mann-Whitney U rank test for two independent samples.
- STEP-4: Compute the p-value and fix value of alpha. We set our alpha to be 0.05

- STEP-5: Compare p-value and alpha. Based on p-value, we will accept or reject H0.

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

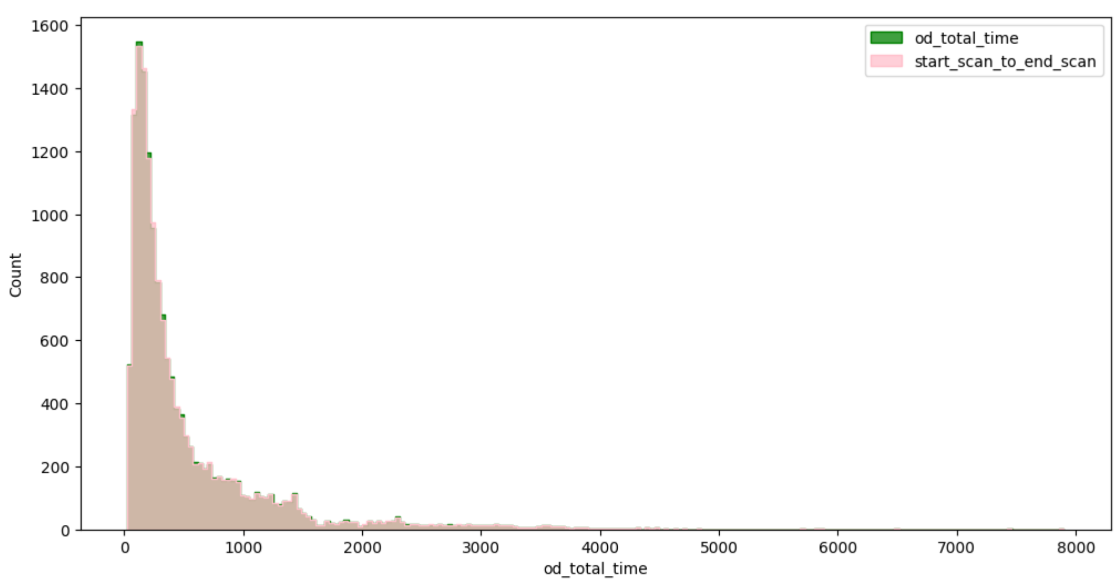
[ ]:
```
df2[['od_total_time', 'start_scan_to_end_scan']].describe()
```

[ ]:
```
       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()
```

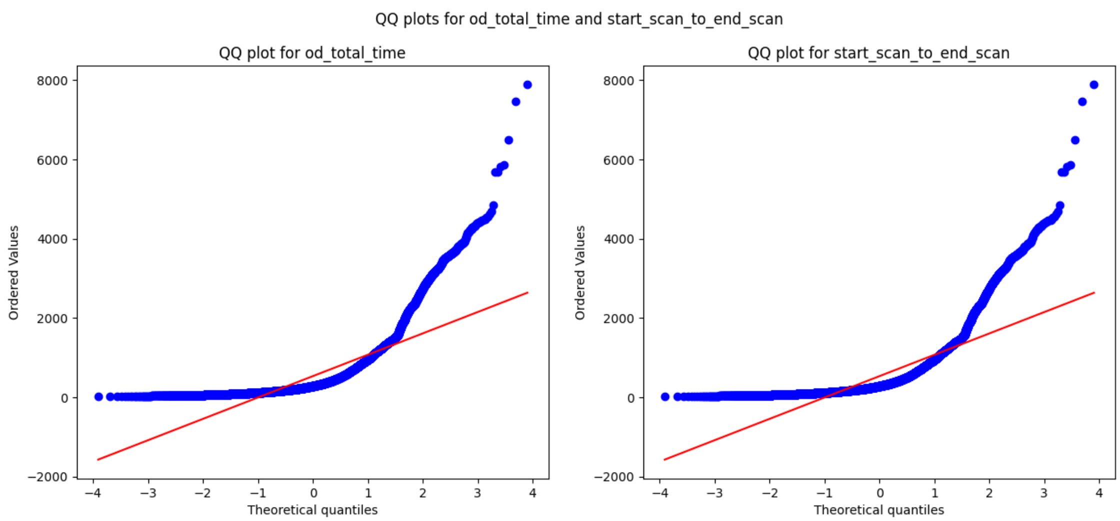
[ ]: []



[ ]:
```
# Distribtion check using of qq plot
import scipy.stats as spy
```

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

[ ]: []



[ ]:
```python
#Applying Shapiro-Wilk test for normality
#ho : The sample follows normal distribution
#ha : The sample does not follow normal distribution

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
```

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

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

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

[ ]:
```
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
```

[ ]:
```
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(HO) - 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.

visual analysis between actual_time aggregated value and OSRM time aggregated value

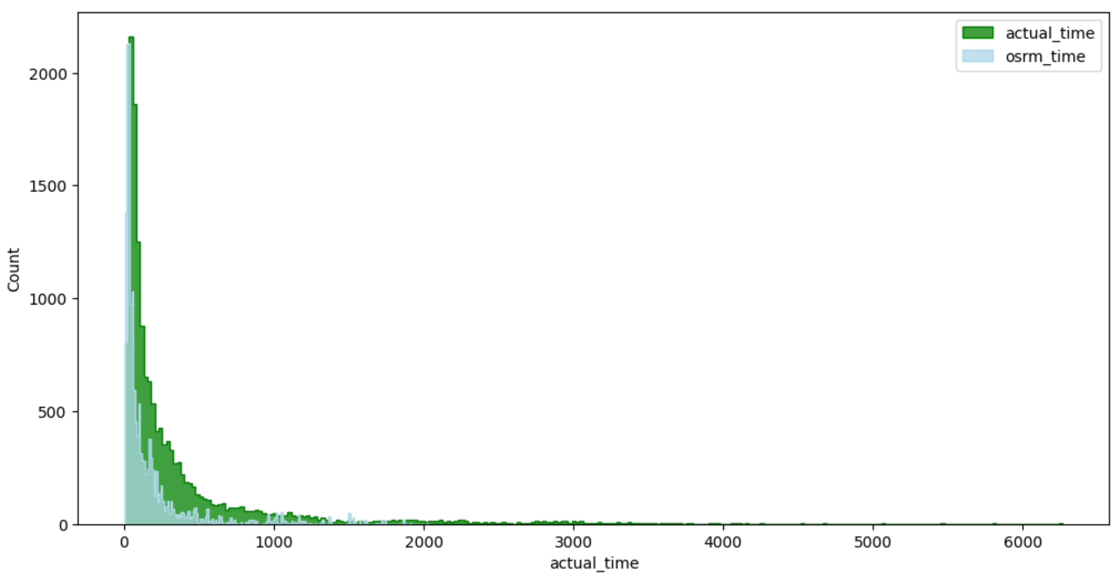
[ ]:
```
df2[['actual_time', 'osrm_time']].describe()
```

[ ]:

	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

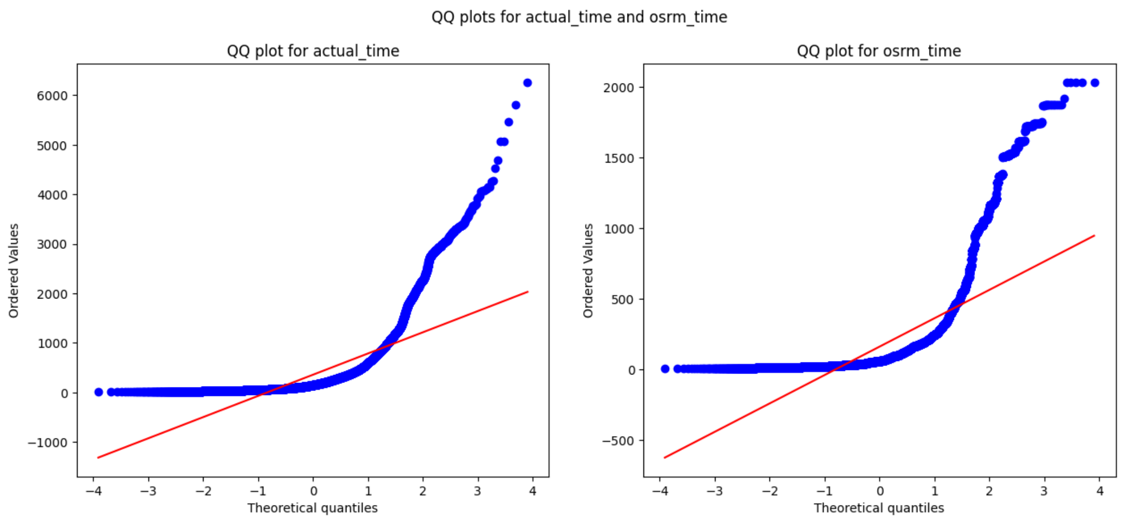
[ ]:
```
plt.figure(figsize = (12, 6))
sns.histplot(df2['actual_time'], element = 'step', color = 'green')
sns.histplot(df2['osrm_time'], element = 'step', color = 'lightblue')
plt.legend(['actual_time', 'osrm_time'])
plt.plot()
```

[ ]: []



[ ]:
```
#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

[ ]:
```
#Applying Shapiro-Wilk test for normality
#ho : The sample follows normal distribution
#ha : The sample does not follow normal distribution

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
```

```
[ ]: 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
```

The sample does not follow 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
```

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
```

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
```

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

visual analysis between actual_time aggregated value and segment actual time aggregated value

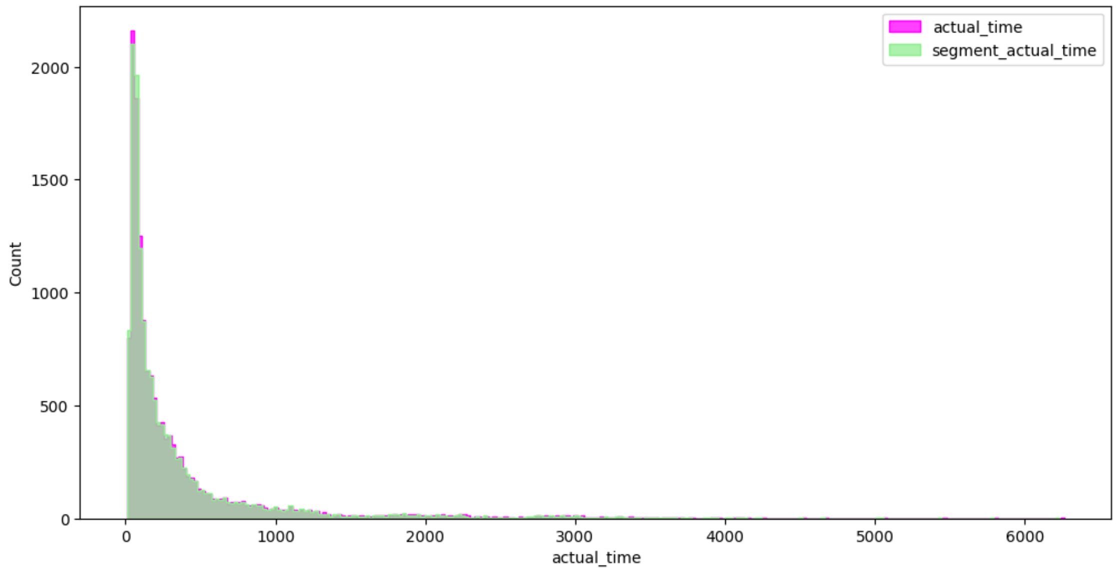
[ ]:
```
df2[['actual_time', 'segment_actual_time']].describe()
```

[ ]:

	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

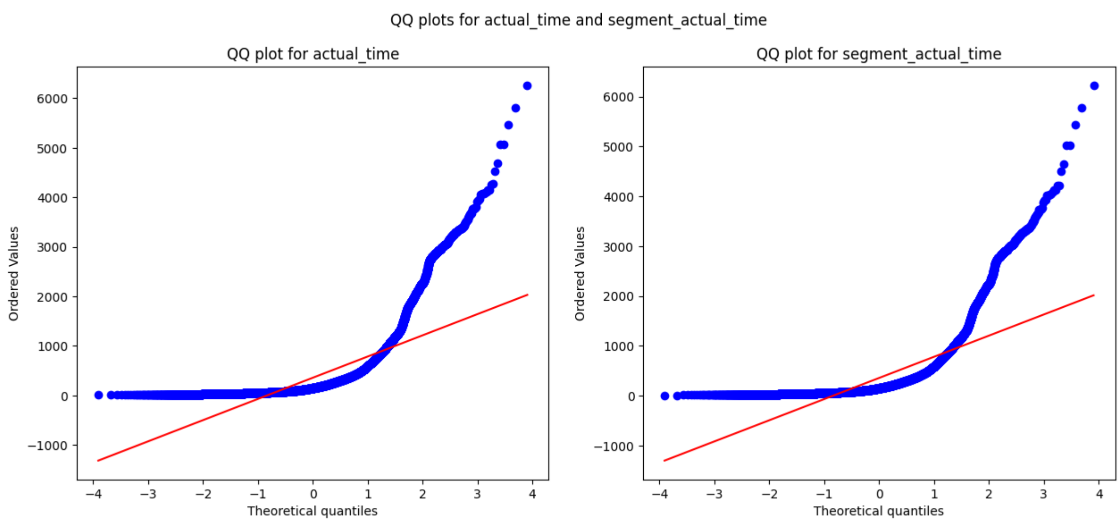
[ ]:
```
plt.figure(figsize = (12, 6))
sns.histplot(df2['actual_time'], element = 'step', color = 'magenta')
sns.histplot(df2['segment_actual_time'], element = 'step', color = 'lightgreen')
plt.legend(['actual_time', 'segment_actual_time'])
plt.plot()
```

[ ]: []



[ ]:
```python
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()
```

[ ]: []



[ ]:
```
#Applying Shapiro-Wilk test for normality
#ho : The sample follows normal distribution
#ha : The sample does not follow normal distribution

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
```

The sample does not follow normal distribution Transforming the data using boxcox transformation to check if the transformed data follows normal distribution.

[ ]:
```
#ho : The sample follows normal distribution
#ha : The sample does not follow 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
```

[ ]:
```
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(HO) - 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
```

visual analysis between osrm distance aggregated value and segment osrm distance aggregated value

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

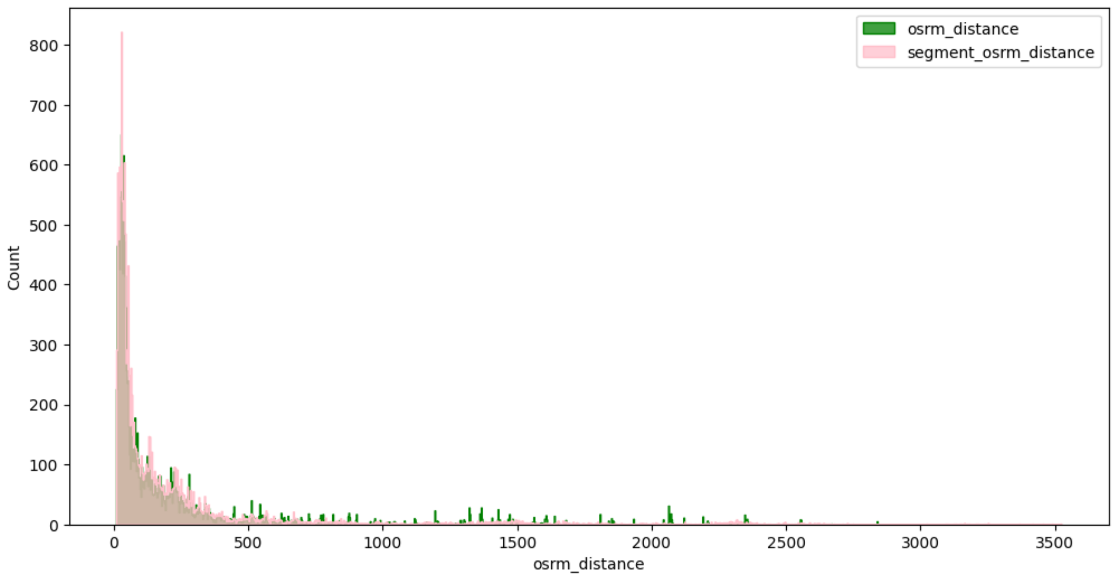
[ ]:

	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

the samples follow normal distribution

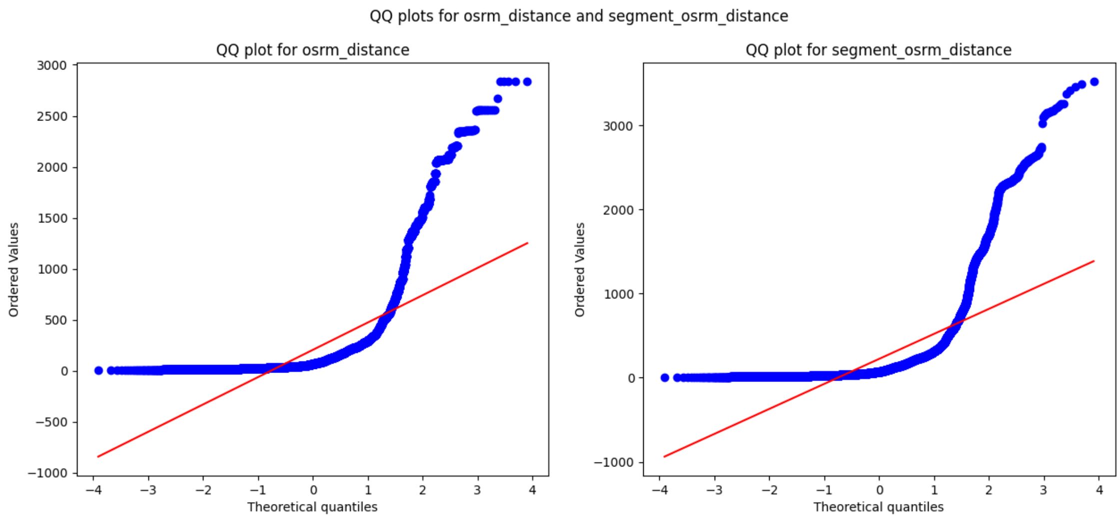
[ ]:
```
plt.figure(figsize = (12, 6))
sns.histplot(df2['osrm_distance'], element = 'step', color = 'green', bins =␣
 ↪1000)
sns.histplot(df2['segment_osrm_distance'], element = 'step', color = 'pink',␣
 ↪bins = 1000)
plt.legend(['osrm_distance', 'segment_osrm_distance'])
plt.plot()
```

[ ]: []



[ ]:
```
# 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()
```

[ ]: []



[ ]:
```
#Applying Shapiro-Wilk test for normality
#ho : The sample follows normal distribution
#ha : The sample does not follow normal distribution
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
```

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
```

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
```

The sample does not follow normal distribution

```
[ ]: 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
```

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(HO) - 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
```

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_time and segment_osrm_time are not similar

Find outliers in the numerical 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
```

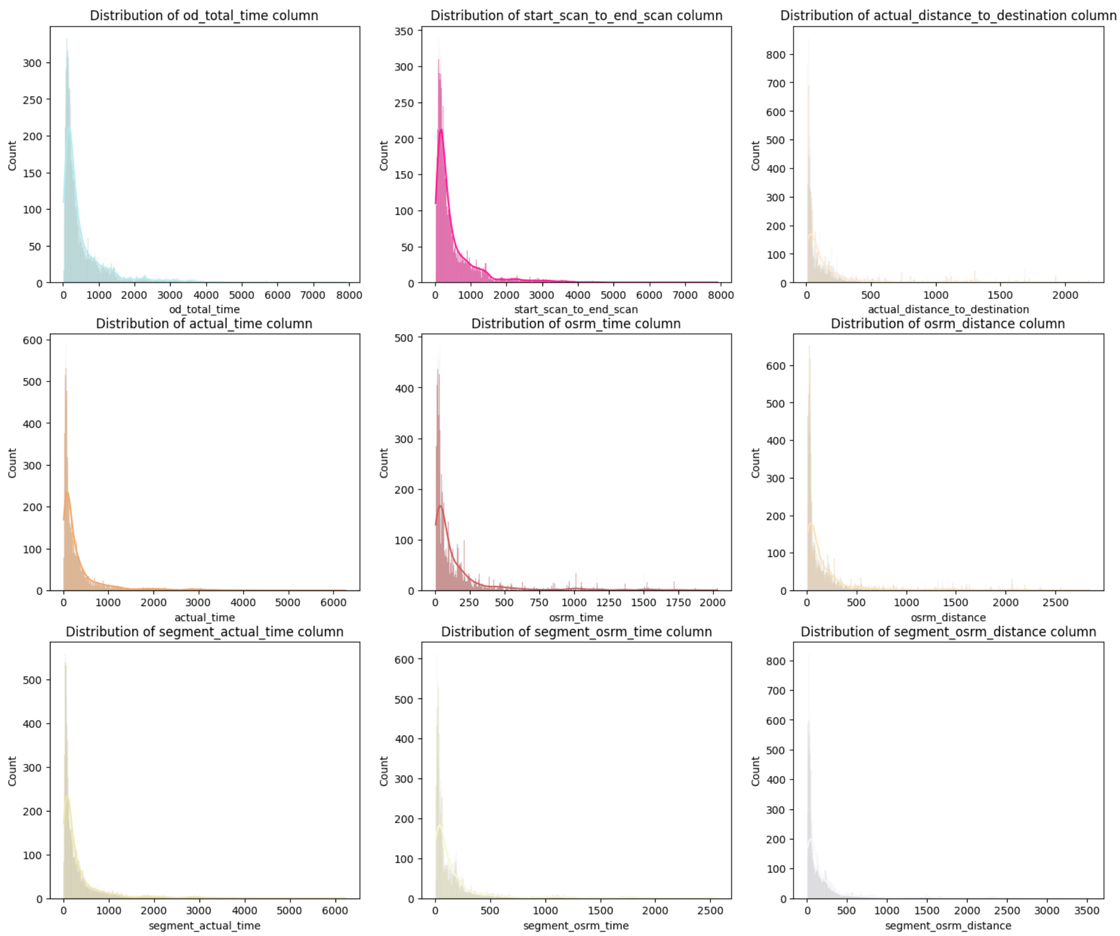
[ ]:
```
                                  count        mean         std        min  \
od_total_time                   14817.0  531.697630  658.868223  23.460000
start_scan_to_end_scan          14817.0  530.810016  658.705957  23.000000
actual_distance_to_destination  14817.0  164.477829  305.388153   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
```

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

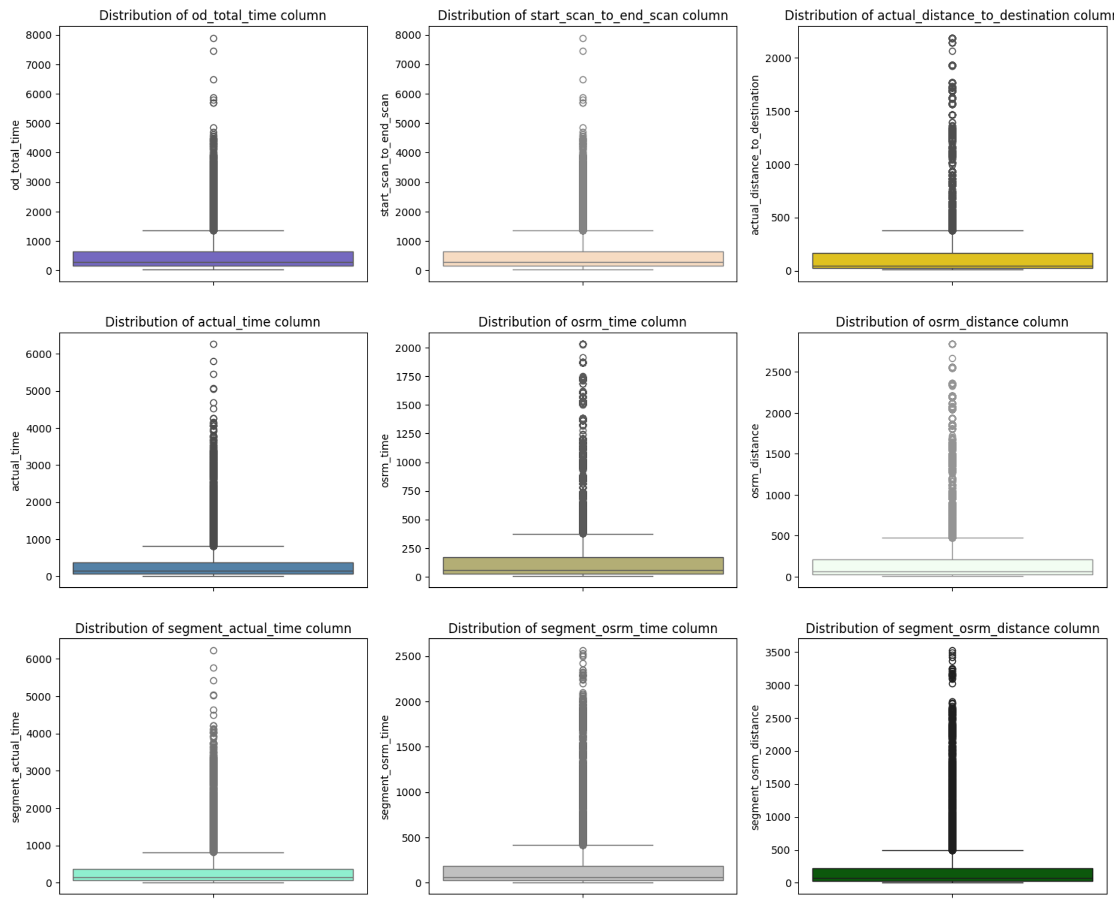


It can be inferred from the above plots that data in all the numerical columns are right skewed.

Outlier Treatment

[ ]:
```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.

[ ]:
```
# 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}')
```

```python
    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

one-hot encoding of categorical variables (like route_type)

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

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

[ ]:
```python
# 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()
```

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

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

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

[ ]:
```
# Perform one-hot encoding on categorical variable 'data'
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
df2['data'] = label_encoder.fit_transform(df2['data'])
```

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

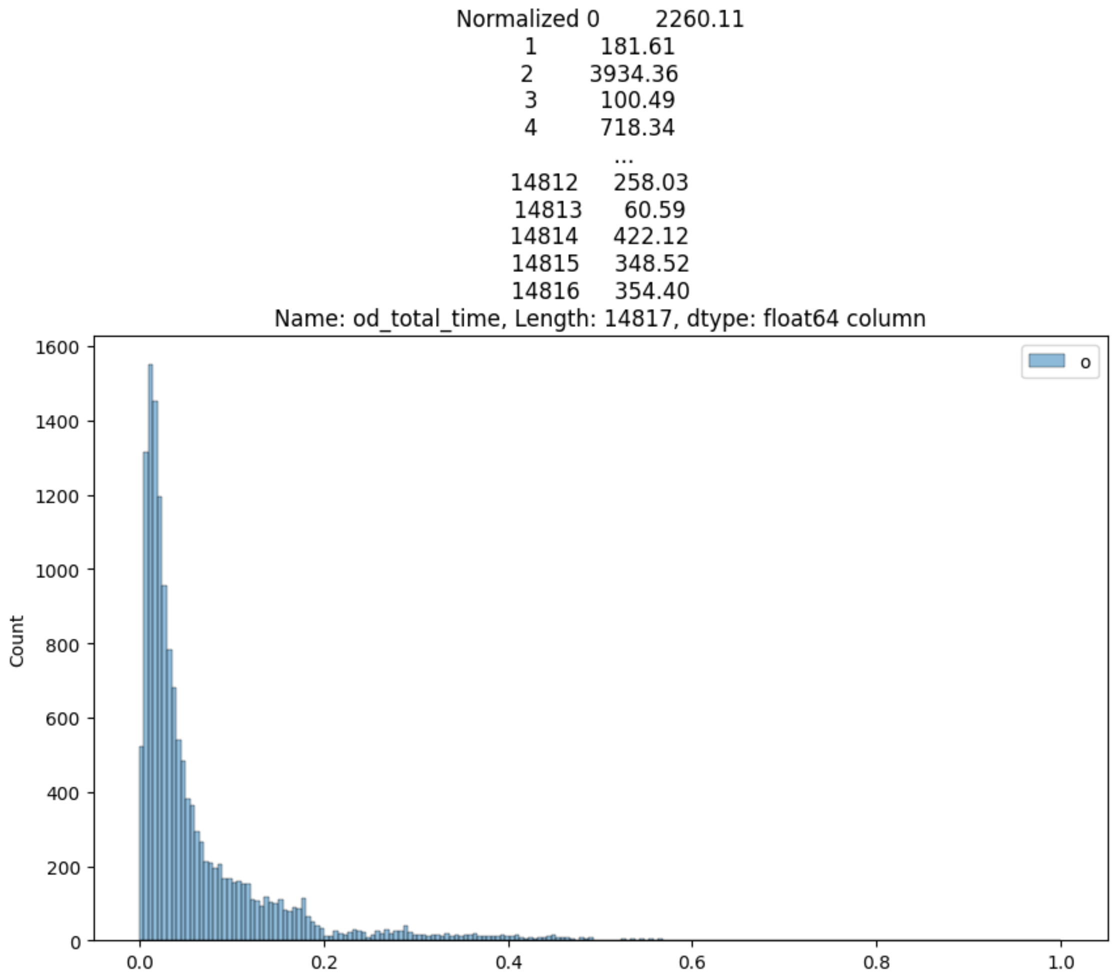
[ ]:
```
data
1    10654
0     4163
Name: count, dtype: int64
```

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()
```

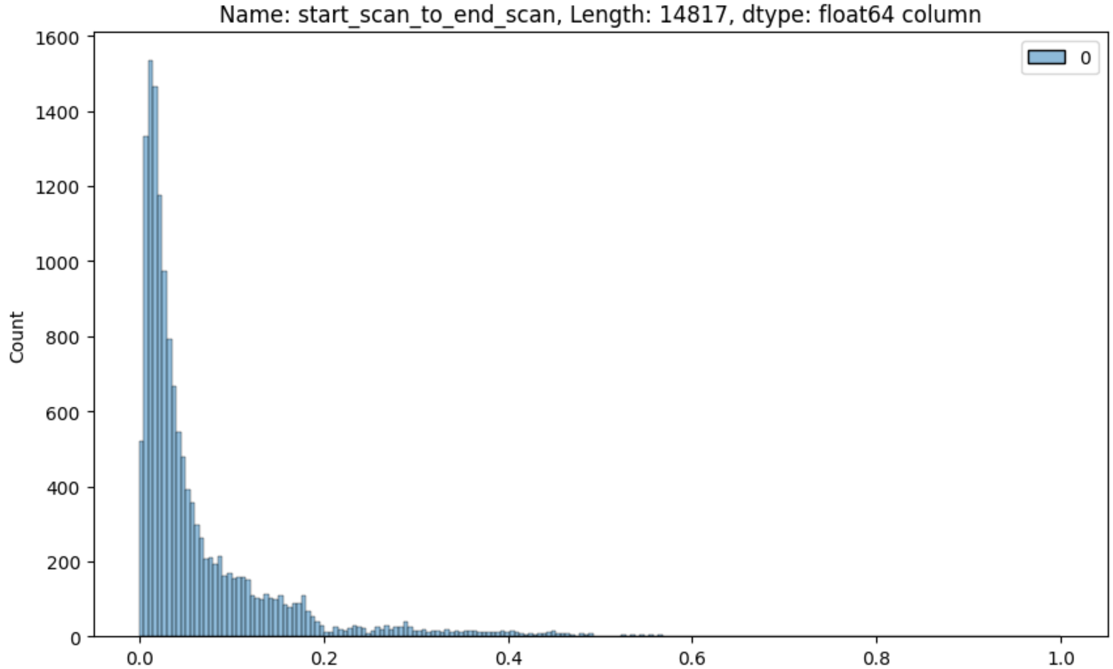
[ ]:
```
[]
```




```
[ ]: 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()
```

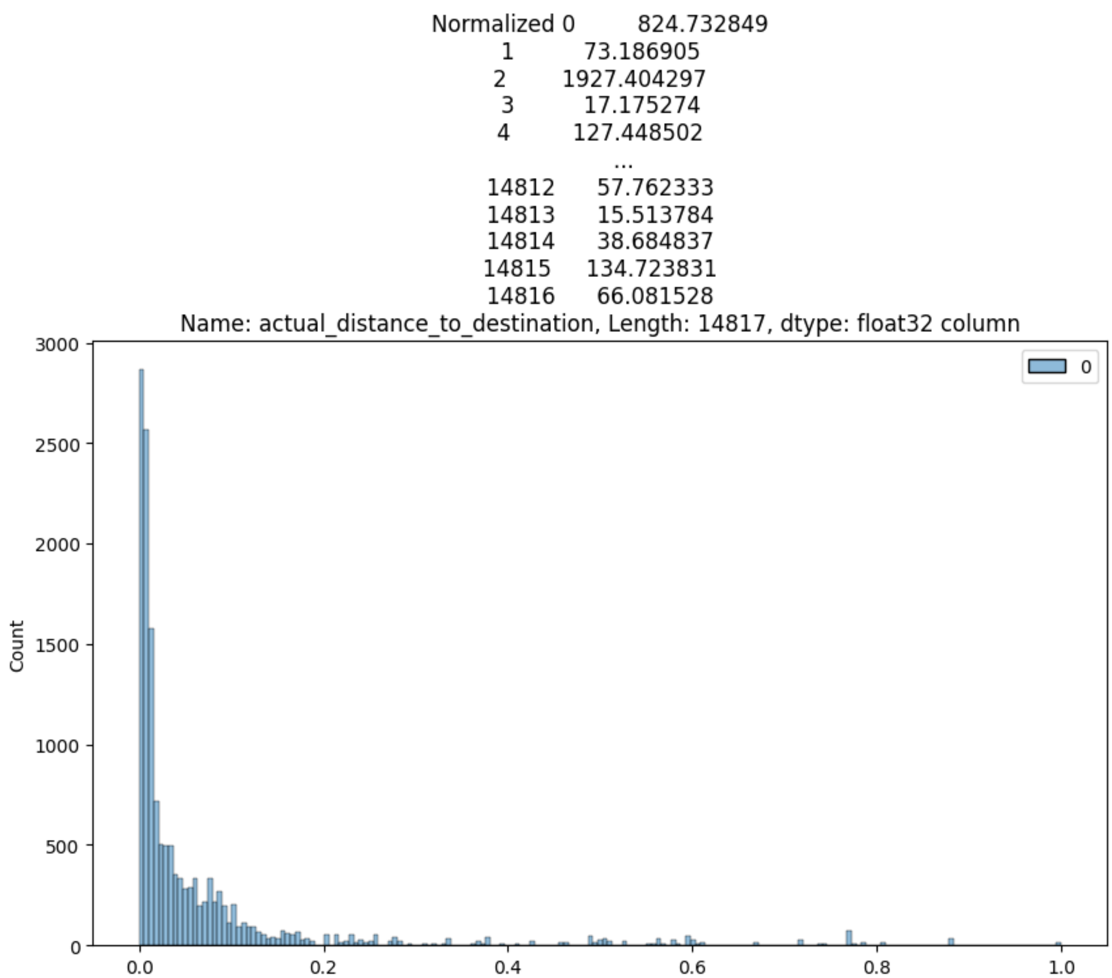
```
[ ]: []
```

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



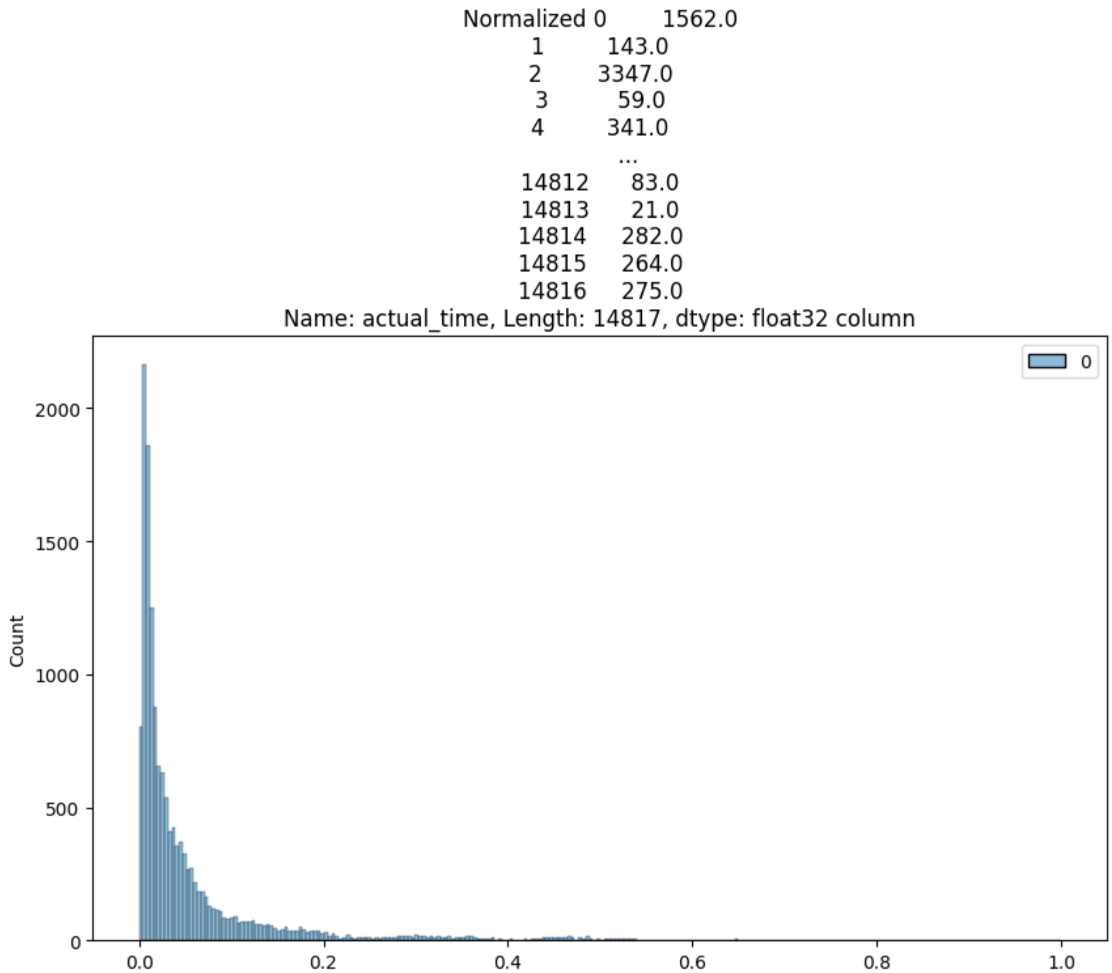
[ ]:
```python
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['actual_distance_to_destination'].to_numpy().
 ↪reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['actual_distance_to_destination']} column")
plt.plot()
```

[ ]: []



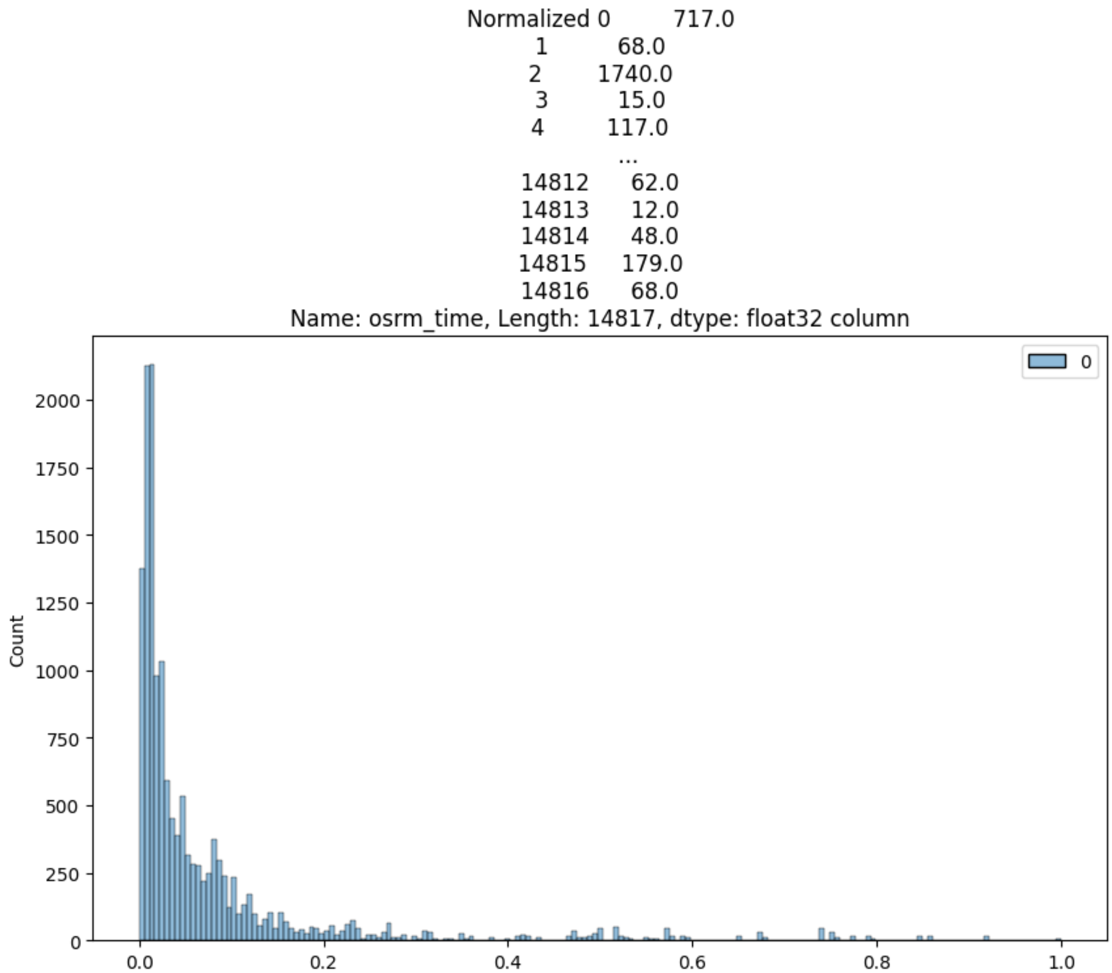
[ ]:
```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['actual_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['actual_time']} column")
plt.plot()
```

[ ]:
```
[]
```



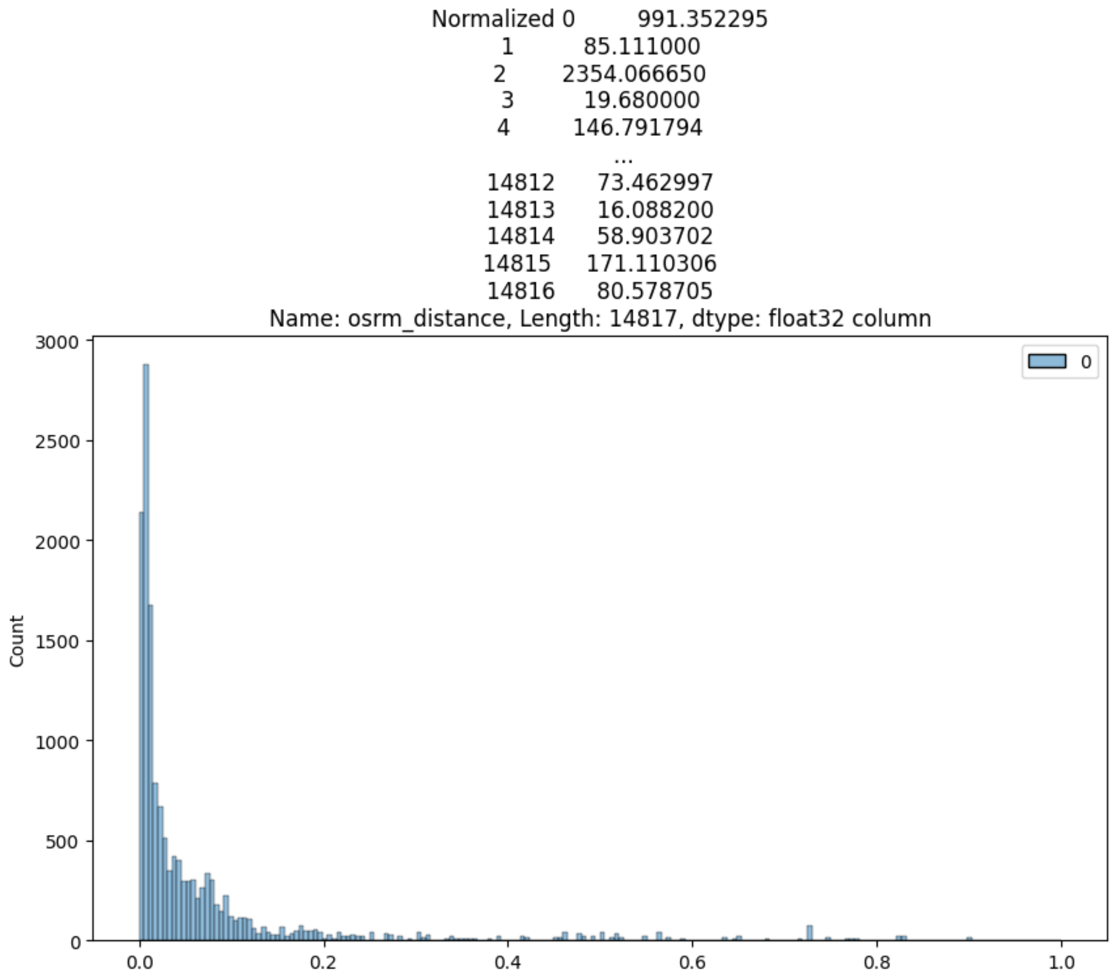

```
[ ]: plt.figure(figsize = (10, 6))
     scaler = MinMaxScaler()
     scaled = scaler.fit_transform(df2['osrm_time'].to_numpy().reshape(-1, 1))
     sns.histplot(scaled)
     plt.title(f"Normalized {df2['osrm_time']} column")
     plt.plot()
```

```
[ ]: []
```



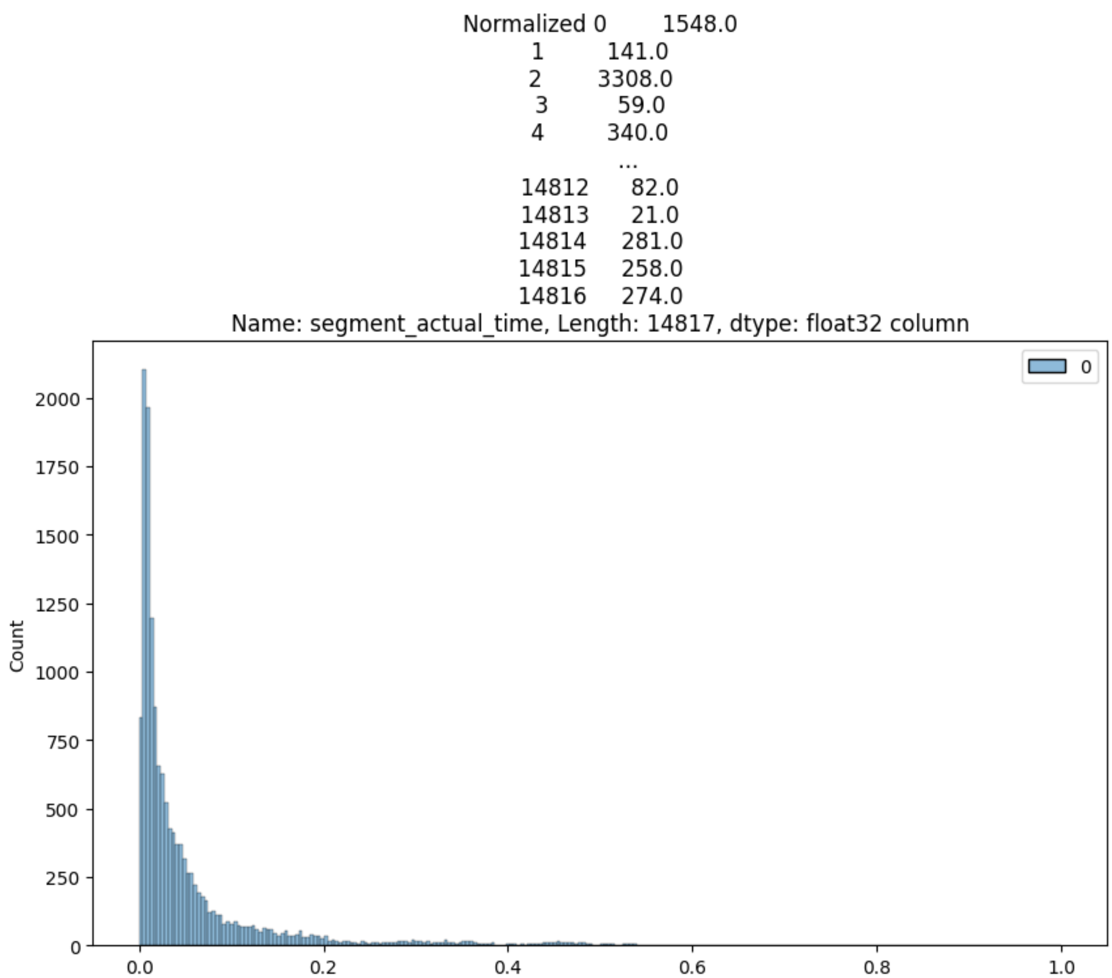
[ ]:
```
plt.figure(figsize = (10, 6))
scaler = MinMaxScaler()
scaled = scaler.fit_transform(df2['osrm_distance'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Normalized {df2['osrm_distance']} column")
plt.plot()
```

[ ]: []



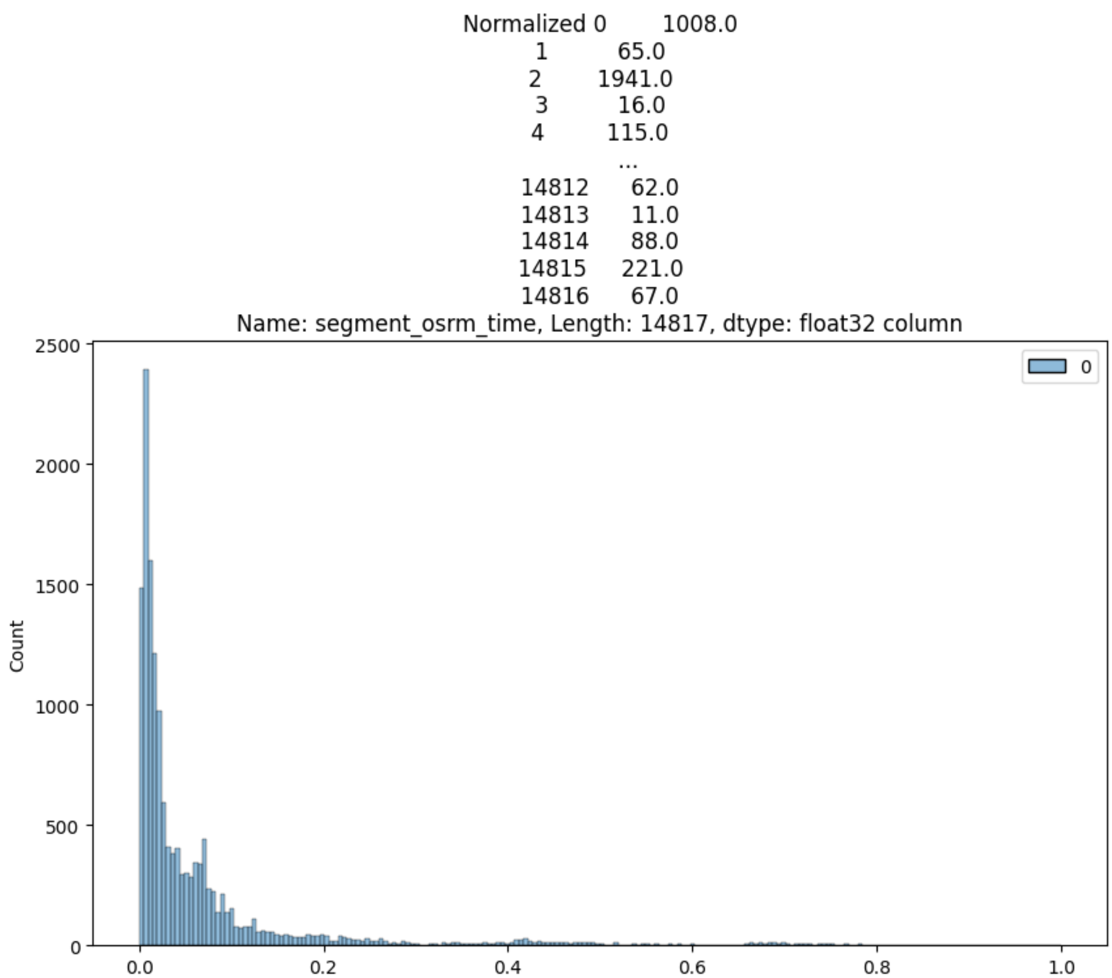

```
[ ]: plt.figure(figsize = (10, 6))
     scaler = MinMaxScaler()
     scaled = scaler.fit_transform(df2['segment_actual_time'].to_numpy().reshape(-1,␣
      ↪1))
     sns.histplot(scaled)
     plt.title(f"Normalized {df2['segment_actual_time']} column")
     plt.plot()
```

```
[ ]: []
```



[ ]:
```
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()
```

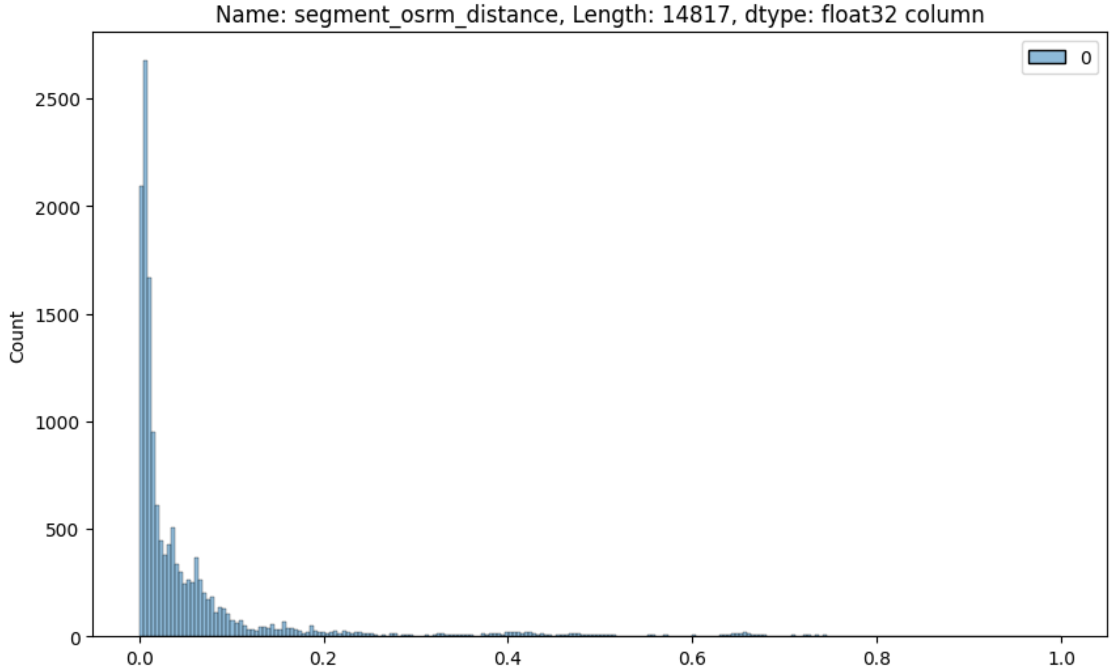
[ ]: []



[ ]:
```
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()
```

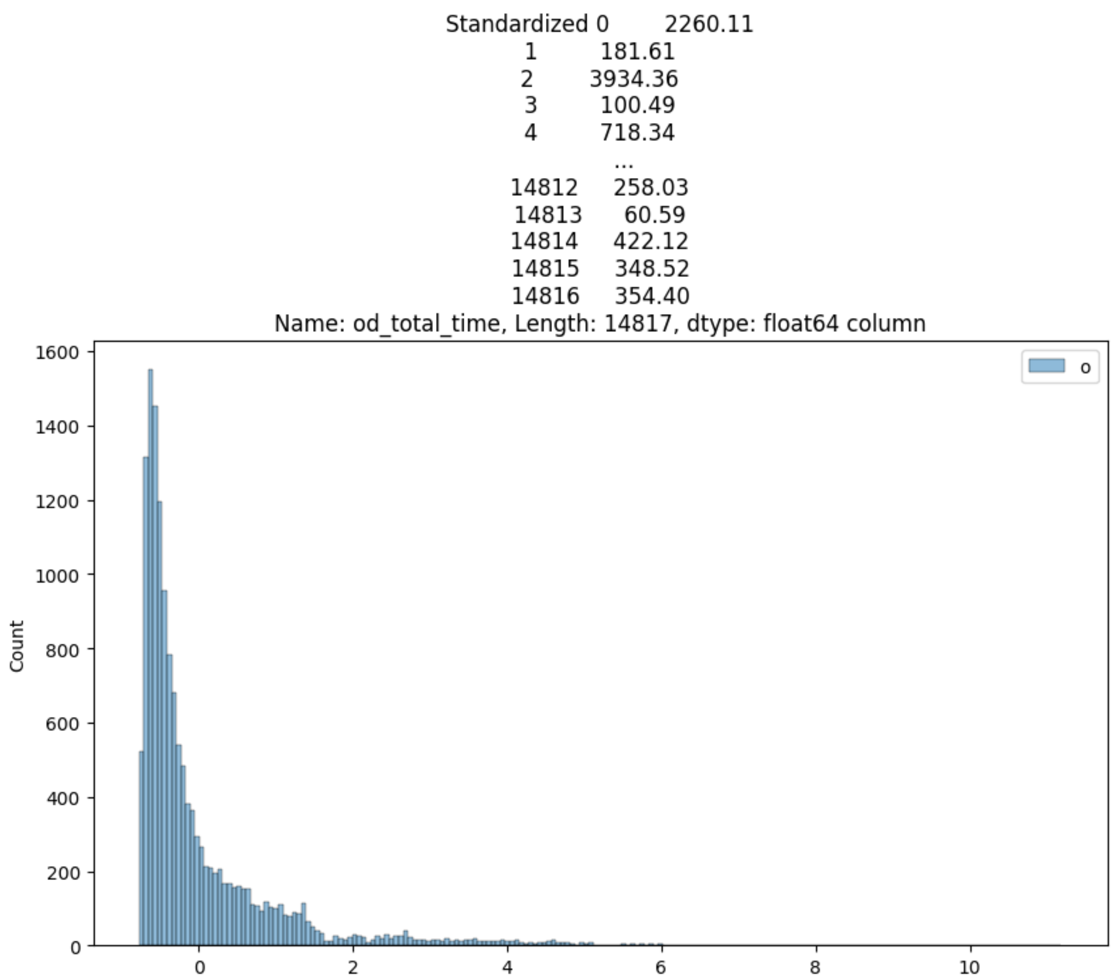
[ ]: []

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



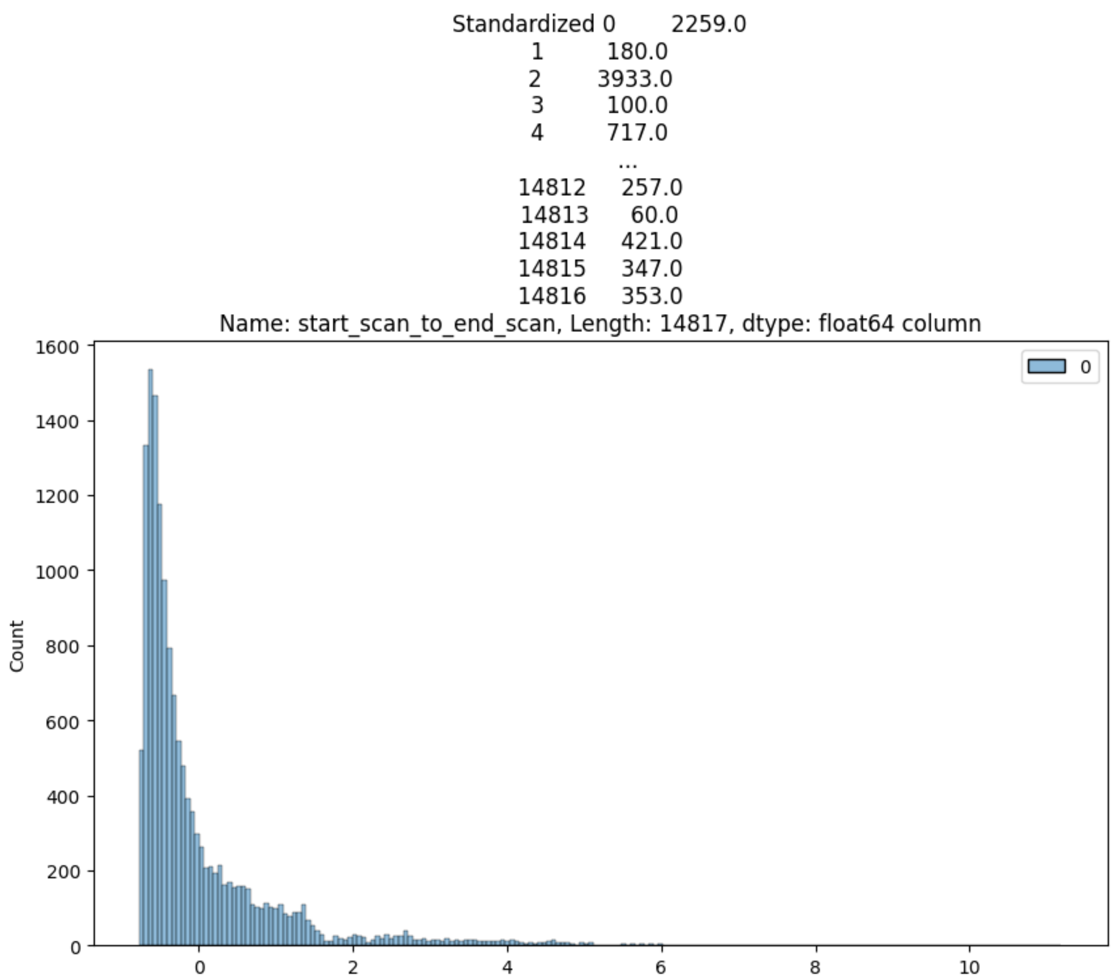
[ ]:
```
from sklearn.preprocessing import StandardScaler
plt.figure(figsize = (10, 6))
# define standard scaler
scaler = StandardScaler()
# transform data
scaled = scaler.fit_transform(df2['od_total_time'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['od_total_time']}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

[ ]: []



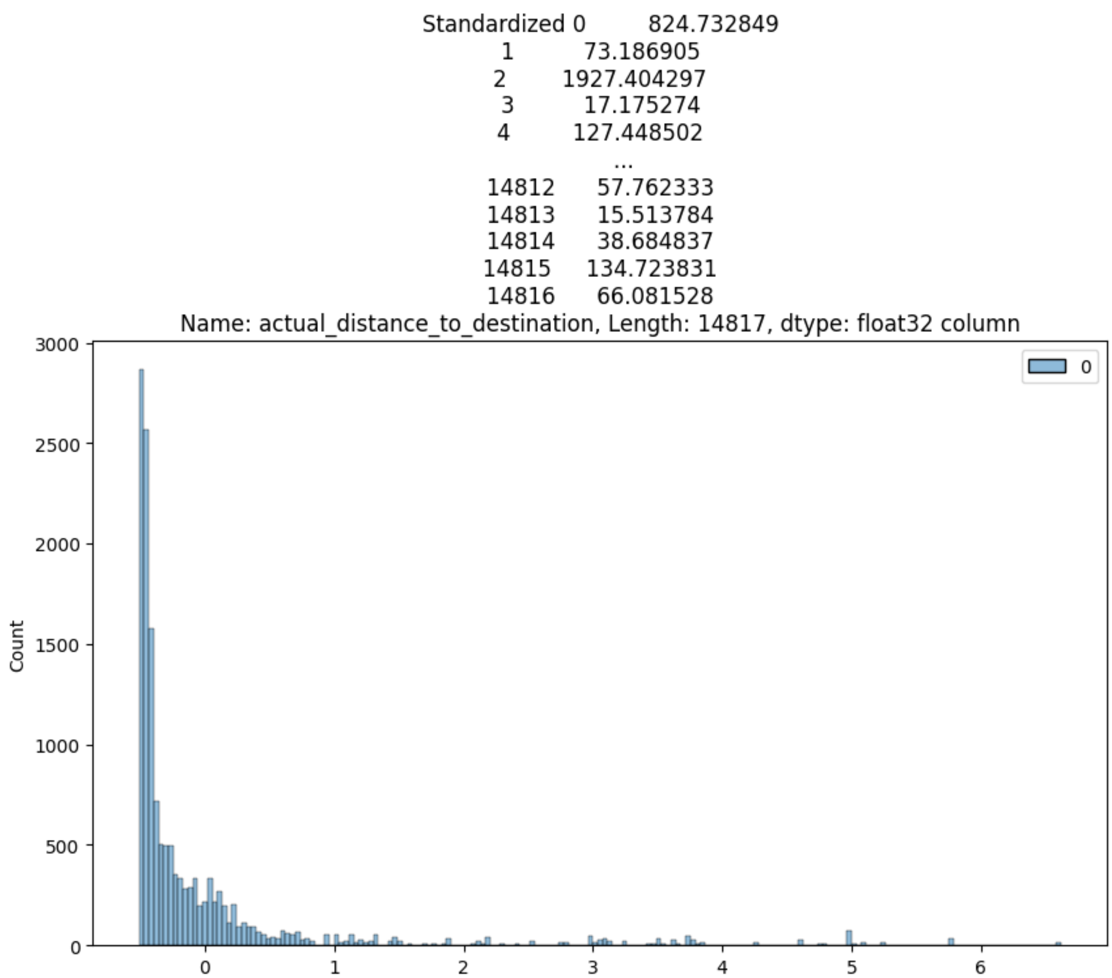

```
[ ]: plt.figure(figsize = (10, 6))
     scaler = StandardScaler()
     scaled = scaler.fit_transform(df2['start_scan_to_end_scan'].to_numpy().
      ↪reshape(-1, 1))
     sns.histplot(scaled)
     plt.title(f"Standardized {df2['start_scan_to_end_scan']} column")
     plt.plot()
```

```
[ ]: []
```



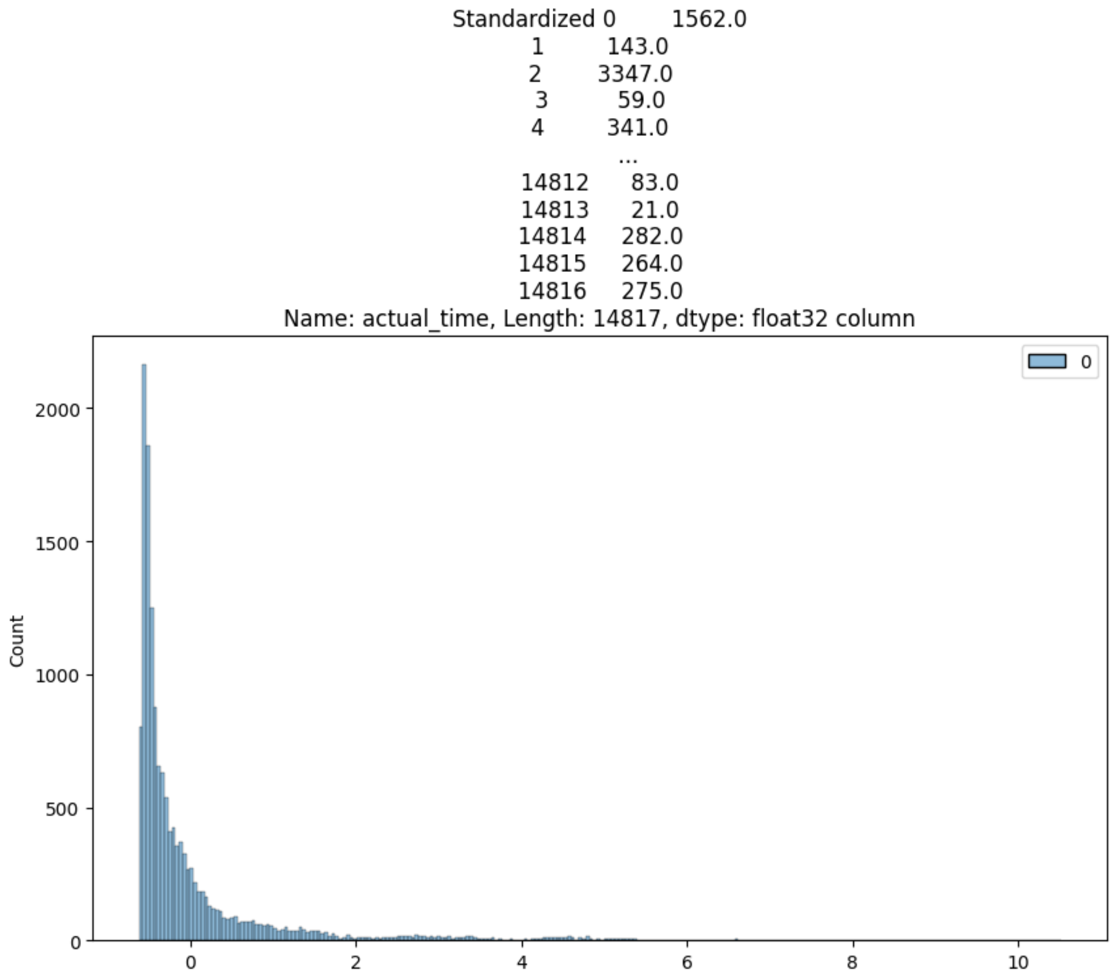
[ ]:
```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['actual_distance_to_destination'].to_numpy().
 ↪reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['actual_distance_to_destination']} column")
plt.plot()
```

[ ]: []




```
[ ]: 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()
```

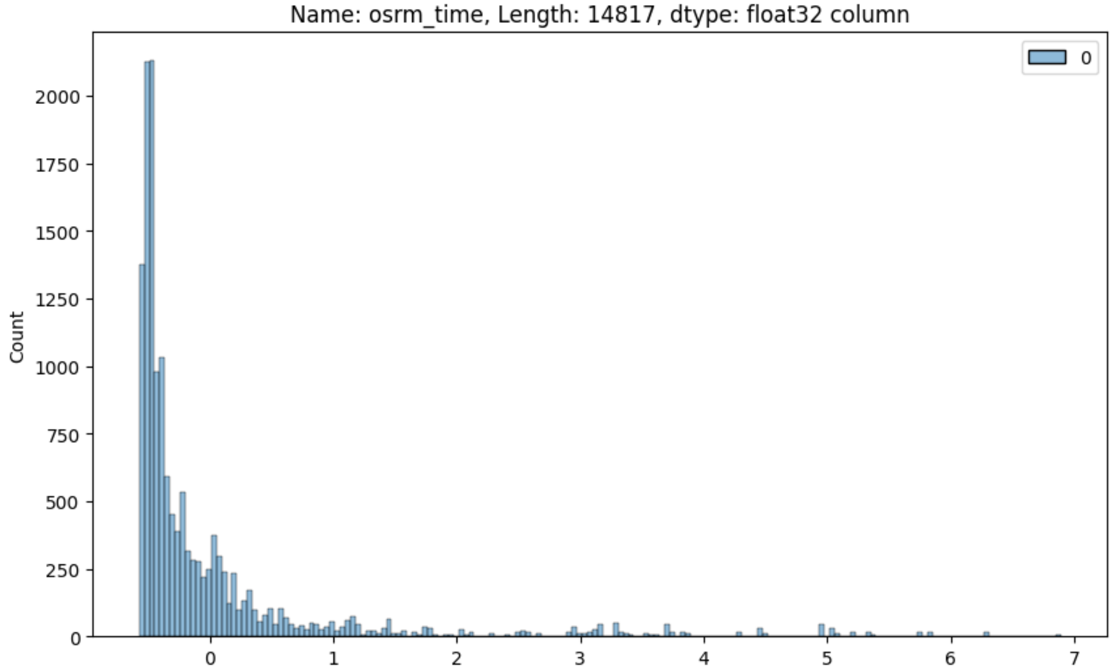
```
[ ]: []
```



[ ]:
```
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()
```

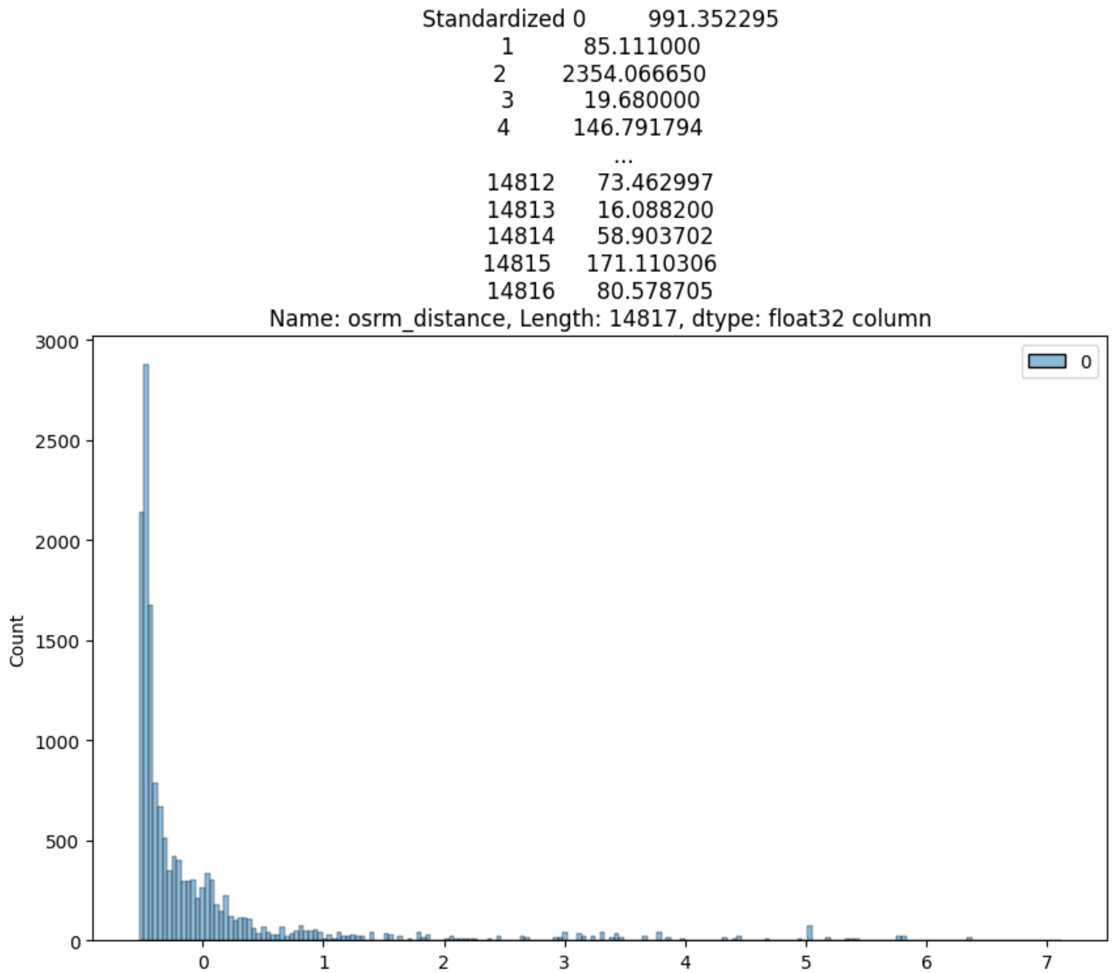
[ ]: []

```
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
```



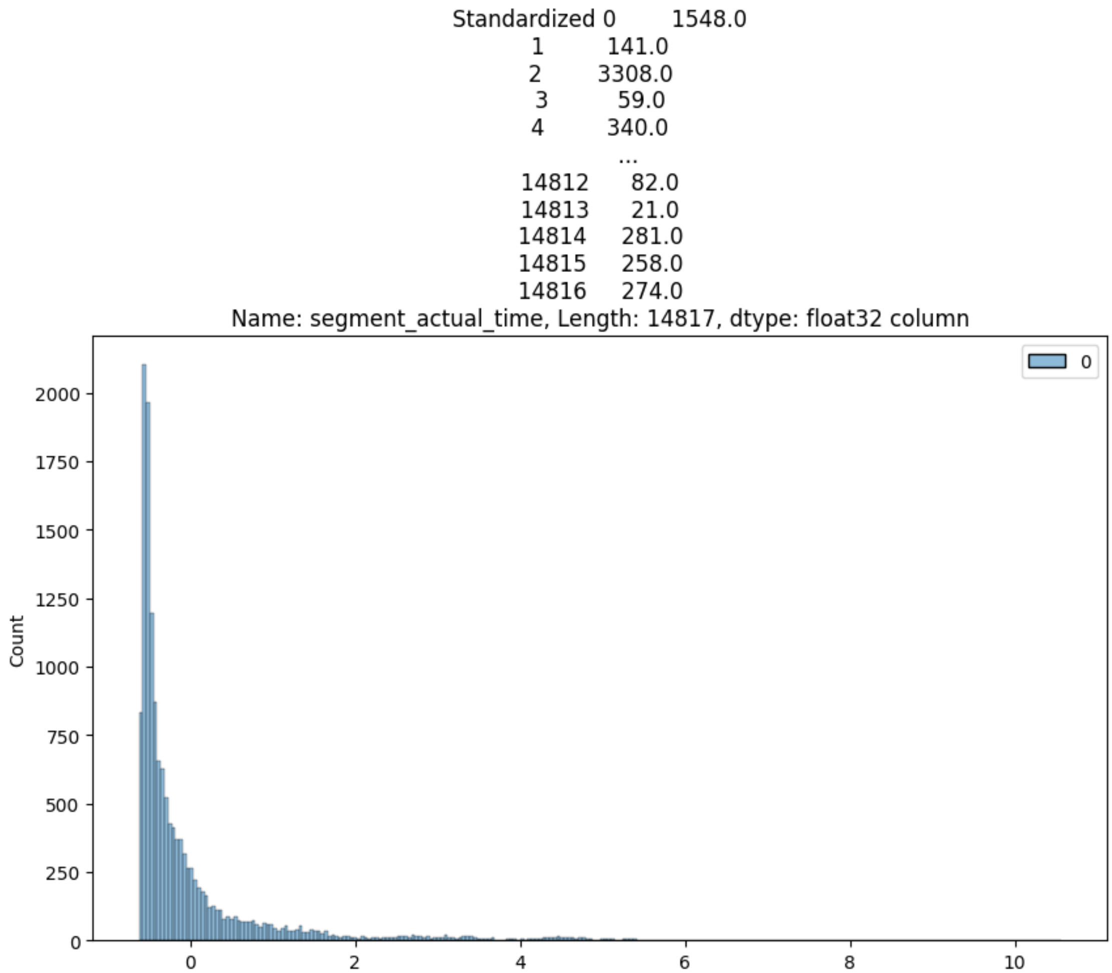
[ ]:
```python
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['osrm_distance'].to_numpy().reshape(-1, 1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['osrm_distance']} column")
plt.plot()
```

[ ]:
```
[]
```



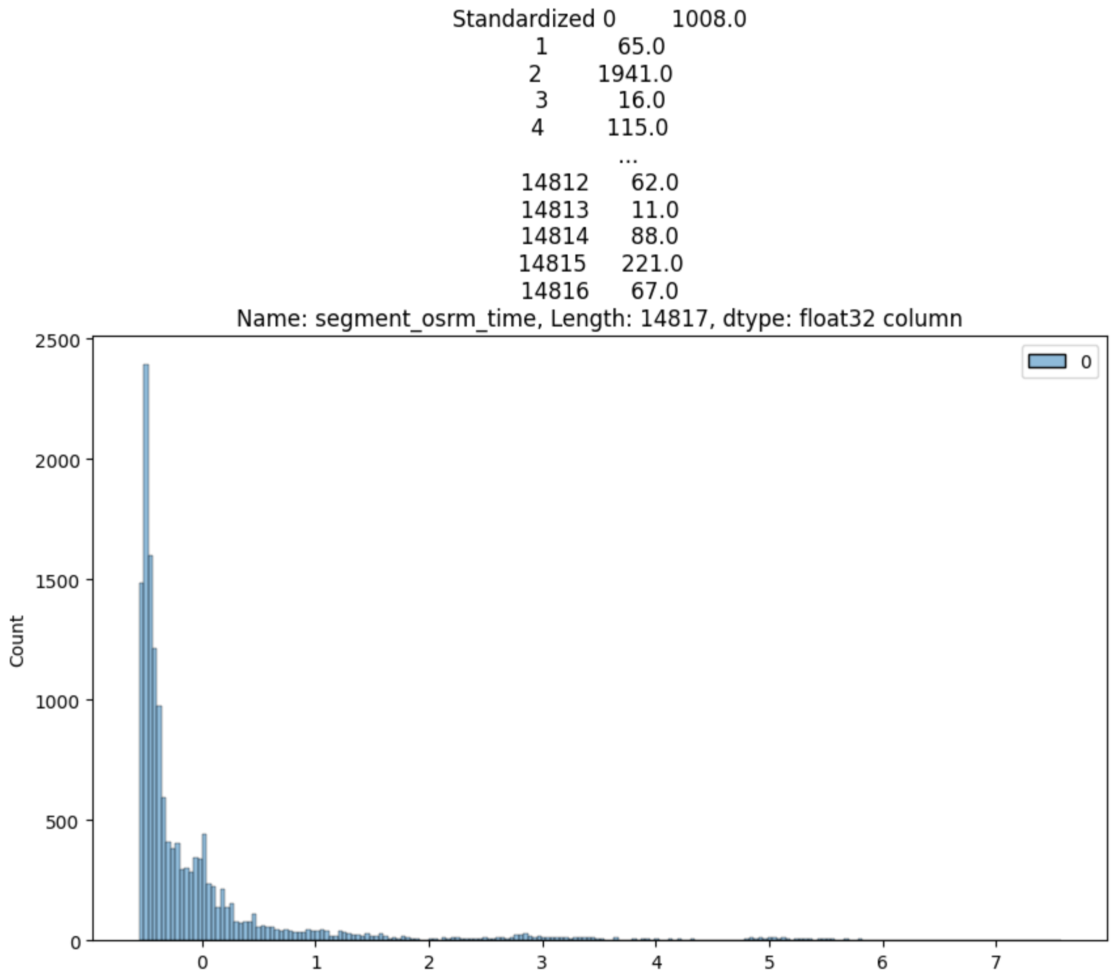
[ ]:
```
plt.figure(figsize = (10, 6))
scaler = StandardScaler()
scaled = scaler.fit_transform(df2['segment_actual_time'].to_numpy().reshape(-1,␣
↪1))
sns.histplot(scaled)
plt.title(f"Standardized {df2['segment_actual_time']} column")
plt.plot()
```

[ ]: []



[ ]:
```
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()
```

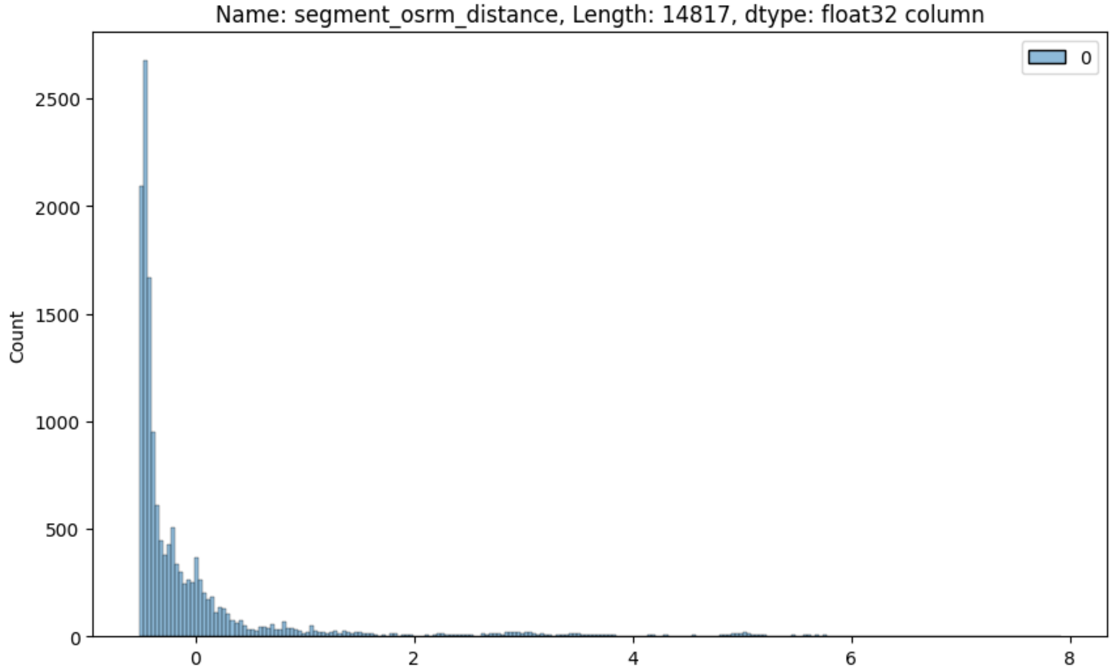
[ ]: []



[ ]:
```
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 data is given from the period '2018-09-12 00:00:16' to '2018-10-08 03:00:24'.
- There are about 14817 unique trip IDs, 1508 unique source centers, 1481 unique destination_centers, 690 unique source cities, 806 unique destination cities.
- Most of the data is for testing than for training.
- Most common route type is Carting.
- The names of 14 unique location ids are missing in the data.
- The number of trips start increasing after the noon, becomes maximum at 10 P.M and then start decreasing.
- Maximum trips are created in the 38th week.
- Most orders come mid-month. That means customers usually make more orders in the mid of the month.

- Most orders are sourced from the states like Maharashtra, Karnataka, Haryana, Tamil Nadu, Telangana
- Maximum number of trips originated from Mumbai city followed by Gurgaon Delhi, Bengaluru and Bhiwandi. That means that the seller base is strong in these cities.
- Maximum number of trips ended in Maharashtra state followed by Karnataka, Haryana, Tamil Nadu and Uttar Pradesh. That means that the number of orders placed in these states is significantly high.
- Maximum number of trips ended in Mumbai city followed by Bengaluru, Gurgaon, Delhi and Chennai. That means that the number of orders placed in these cities is significantly high.
- Most orders in terms of destination are coming from cities like bengaluru, mumbai, gurgaon, bangalore, Delhi.
- Features start_scan_to_end_scan and od_total_time(created feature) are statistically similar.
- Features actual_time & osrm_time are statitically different.
- Features start_scan_to_end_scan and segment_actual_time are statistically similar.
- Features osrm_distance and segment_osrm_distance are statistically different from each other.
- Both the osrm_time & segment_osrm_time are not statistically same.

Recommendations

- The data suggests a seasonal pattern where September experiences higher trip activity. This could be due to various factors such as weather conditions, holidays, or special events.
- The OSRM trip planning system needs to be improved. Discrepancies need to be catered to for transporters, if the routing engine is configured for optimum results.
- The OSRM trip planning system needs to be improved. Discrepancies need to be catered to for transporters, if the routing engine is configured for optimum results.
- The osrm distance and actual distance covered are also not same i.e. maybe the delivery person is not following the predefined route which may lead to late deliveries or the osrm devices is not properly predicting the route based on distance, traffic and other factors. Team needs to look into it.
- Most of the orders are coming from/reaching to states like Maharashtra, Karnataka, Haryana and Tamil Nadu. The existing corridors can be further enhanced to improve the penetration in these areas.
- Customer profiling of the customers belonging to the states Maharashtra, Karnataka, Haryana, Tamil Nadu and Uttar Pradesh has to be done to get to know why major orders are coming from these atates and to improve customers' buying and delivery experience.
- From state point of view, we might have very heavy traffic in certain states and bad terrain conditions in certain states.